THE EFFECT OF LEG LENGTH AND STRIDE FREQUENCY ON THE RELIABILITY AND VALIDITY OF ACCELEROMETER DATA

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ABSTRACT

Technological advances in physical activity measurement have increased the development and utilization of accelerometers and pedometers for assessing physical activity in controlled and free-living conditions. Individual differences in leg length, stride length and stride frequency may affect the reliability and validity of accelerometers in estimating energy expenditure. To address this theory, this thesis investigated the influence of leg length, stride length and stride frequency on accelerometer counts and energy expenditure using four accelerometers (AMP, Actical, MTI, and RT3) and one pedometer (Yamax). Eighty-six participants, age 8 to 40 (17.6 ± 8.0) years performed three ten-minute bouts of treadmill activity at self-selected speeds (4 to 12 km/h). Energy expenditure (kcal/min) was measured through expired gas analysis and used as the criterion standard to compare physical activity data from activity monitors. A 3 (models) x 2 (duplicates of each model) x 3 (speeds) x 7 (minutes) repeated measures ANOVA was used to assess intra-device, inter-device, and inter-model reliability. Coefficients of variation were calculated to compare within-device variation and between-device variation in accelerometer counts. Differences between measured and predicted energy expenditure were assessed across five height categories to determine the influence of leg length on the validity of accelerometer/pedometer data. Regression equations for each model were developed using mean activity counts/steps generated for each speed, adjusting for various predictor variables (i.e., age, weight, leg length). These were compared to model-specific equations to determine whether the addition of certain variables might explain more variance in energy expenditure. Leg length and stride frequency directly

influenced variability in accelerometer data and thus predicted energy expenditure. At high speeds and stride frequencies counts began to level off in the Actical, however this did not occur in the other devices. Intra-device and inter-device variation in accelerometer counts was less than 10% and was lowest at very high speeds for the Actical, MTI, and RT3 ($p<0.05$). When compared to measured values, energy expenditure was consistently underestimated by the AMP, Actical, and Yamax models and consistently overestimated by the RT3 across speed. The MTI underestimated and overestimated energy expenditure depending on speed. Energy expenditure was both underestimated and overestimated to the greatest extent during the treadmill run for the tallest participants ($p<0.05$). Accelerometer counts or pedometer steps, when entered into regression equations with age, weight and leg length, explained from 85 to 94 % of the variance in measured energy expenditure, supporting the inclusion of these variables within manufacturer-based equations. These results suggest that individual differences in leg length and stride frequency affect the reliability and validity of accelerometer data and therefore must be controlled for when using accelerometry to predict energy expenditure.

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DEDICATION

This thesis is dedicated to my parents, Ann and Michael Stone, for teaching me the value of education and the importance of believing in myself and my ambitions. By providing unconditional encouragement and support, they have made it possible for me to embrace new surroundings and challenges that have brought many great experiences. The opportunities they have provided me with are extremely appreciated, and their interest in helping me reach future goals has already, and will continue to make, all the difference.

"Dare to live the life you have dreamed for yourself.

Go forward and make your dreams come true."

--Ralph Waldo Emerson

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SUMMARY OF ACRONYMS USED

64 K	Memory capacity of MTI devices
7DPAR	7-day physical activity recall questionnaire
ACTL	Left Actical device
ACTR	Right Actical device
AEE	Activity induced energy expenditure
AMPL	Left AMP device
AMPR	Right AMP device
BMI	Body mass index; represents weight (kg) divided by height (m^2)
BMR	Basal metabolic rate
cal	Calories
CCHS	Canadian Community Health Survey
CFLRI	Canadian Fitness and Lifestyle Research Institute
CHD	Coronary Heart Disease
cm	Centimeter
CO_2	Carbon dioxide
CSEP	Canadian Society for Exercise Physiology
CV	Coefficient of variation; expresses variation in data relative to the mean of the data set
CV-Intra	Within-device variation in data
CV-Inter	Between-device or between-model variation in data
DEE	Diet induced energy expenditure
DWL	Doubly labeled water; a technique to measure energy expenditure

G	Acceleration; expressed in meters per second squared (m/s^2) or feet per second squared (ft/s^2)
gm	Gram
H^2O^{18}	Hydrogen and oxygen isotopes used with doubly labeled water technique
HPAPQ	Healthy Physical Activity Participation Questionnaire
Hz	Hertz; a measure that reflects the frequency of a periodic phenomenon in one second
ICC	Intra-class correlation coefficient; a measure of inter-device reliability
KKD	Kilocalories per kilogram of body weight per day
kcal	Kilocalories
kg	Kilograms
km/h	Kilometers per hour
km	Kilometers
m/min	Meters per minute
MET	Metabolic equivalent; represents energy (oxygen expenditure), where 1 MET is equivalent to a metabolic rate consuming 3.5 milliliters of oxygen per kilogram of body weight per minute
MTIL	Left MTI device
MTIR	Right MTI device
mmHg	Millimeters of mercury; a reflection of blood pressure
mm	Millimeter
mph	Miles per hour
NHANES	National Health and Nutrition Examination Survey
NHIS	National Health Interview Survey
O_2	Oxygen

p	Statistical measure that denotes significance
PAQ-C	Physical Activity Questionnaire for Older Children
PAR-Q	Physical Activity Readiness Questionnaire
r or R^2	Reliability coefficients; statistical measures that express correlation between two measures
rev/m	Revolutions per minute
RMR	Resting metabolic rate
RT3L	Left RT3 device
RT3R	Right RT3 device
SEE	Standard error of estimate; statistical measure of the accuracy of predictions made using a regression line
SEM	Standard error of mean; statistical measure that reflects the standard deviation of a measure divided by the square root of the number of measurements
SD	Standard deviation; statistical measure representing variation around the mean
sVO_2	Scaled oxygen uptake; to account for differences in body size, oxygen consumption is expressed relative to body mass and raised to the power of 0.75
TEE	Total energy expenditure
V	Volt; measure of activity monitor battery power
VO_2	Measured oxygen consumption
WHO	World Health Organization
YAMAXL	Left Yamax device
YAMAXR	Right Yamax device

CHAPTER ONE: INTRODUCTION

1.1 BACKGROUND

The rising incidence of chronic degenerative disease in the Canadian population has prompted increasing efforts to better understand lifestyle adaptations that have contributed to this phenomenon. Research has indicated that advances in technology have altered, and continue to alter, many occupations and modes of transportation, thus reducing the energy required for daily activities (Montoye, 2000). Consequently, many individuals are becoming less physically active and leading more sedentary lifestyles. Canadian guidelines suggest that 60 minutes of activity a day in periods of at least 10 minutes in length are required to attain the positive health benefits of physical activity (Health Canada, 1998). Evidence from the 2000/01 Canadian Community Health Survey (CCHS) indicates that the majority of Canadians (56%) are physically inactive, accumulating less than three kilocalories per kilogram of body weight per day (KKD) of physical activity (Canadian Fitness and Lifestyle Research Institute, 2004). Moreover, 56% of Canadian children and youth aged 12 to 19 are not sufficiently physically active and as many as 82% may not be active enough to meet international guidelines for optimal growth and development (i.e., an energy expenditure of approximately six to eight KKD; CFLRI, 2004). Research has also identified significant gender differences in physical activity in children, with 64% of girls and 48% of boys under the age of 12 being considered physically inactive (CFLRI, 2004). In 2001, approximately 33% of deaths from cardiovascular disease, colon cancer and type 2 diabetes were attributed to physical inactivity and were responsible for approximately $5.3 billion ($1.6 billion in direct costs, $3.7 billion in indirect costs) to Canada's health care system (Katzmarzyk and Janssen, 2004). This corresponded to 2.6% of all health care costs in Canada that year (Katzmarzyk and Janssen, 2004). Research does however indicate that a 10 percent reduction in the prevalence of inactivity in Canada could lower direct health care costs by $150 million per year (Katzmarzyk, 2000).

The relationship between physical activity and health is well established in past and current literature. Physical activity is a modifiable risk factor for reducing the incidence of many chronic diseases, however the strength of this association is still unknown (Lee and Skerrett, 2001). Individuals who are more physically active and fit appear to have lower risks of all-cause mortality, cardiovascular disease, hypertension, certain cancers, diabetes mellitus and osteoporosis (Kesaniemi et al., 2001). Increases in physical activity and fitness can also offer the positive effects of increased longevity and independent living, improved self-esteem and reduced anxiety and depression (Kesaniemi et al., 2001; Pate et al., 1995). Furthermore, physical activity offers a protective effect against the onset of obesity, now considered as one of the major health threats in the developed world (World Health Organization, 1998).

1.1.1 Obesity

Obesity is classified according to body mass index (BMI); BMI represents weight (kg) divided by height (m^2). Adults with a BMI of 25.0 to 29.9 are considered overweight, while those with a BMI of 30.0 or higher are classified as obese; associated health risks increase directly with any rise in BMI (WHO, 1998). An increase in body weight is a reflection of positive energy balance, where energy input exceeds energy expenditure. Sharp increases in the prevalence of obesity have occurred in the last few decades, especially in the western hemisphere, however also in developing countries (WHO, 1998). Approximately 50% of adults in the United States, Canada and some of the Western European countries have a BMI of 25 or more (WHO, 1998), placing them at increased risk of negative health consequences associated with excess body fat.

What is extremely concerning is the general increase in the prevalence of obesity in childhood and adolescence, a phenomenon that has more than doubled since the early 1960's (Troiano et al., 1995). Tremblay and colleagues (2000) analyzed BMI data collected on Canadian children from 1981 to 1996. The prevalence of overweight rose from 15.0 to 35.4% (boys) and 15.0 to 29.2% (girls), while the prevalence of obesity rose from 5.0 to 16.6% (boys) and 5.0 to 14.6% (girls) across that time span (Tremblay et al., 2000). Comparative increases have also been reported in the United States. Information from the 1999 United States National Health and Nutrition Examination Survey (NHANES) illustrates that 13% of children aged 6 to 11 and 14% of adolescents aged 12 to 19 are obese, an increase of 2-3% from the previous NHANES survey conducted from 1988 to 1994 (Troiano and Flegal, 1998). These increases are especially troubling, as evidence indicates obese children are at increased risk of adult obesity with some estimates suggesting that 33% of adult obesity originates in childhood obesity (Serdula et al., 1993). In the meantime, these children are at an increased risk of heart disease, diabetes, orthopedic problems and various other chronic illnesses, illnesses that will likely proceed into adulthood (Must and Strauss, 1999).

The increase in the prevalence of overweight and obesity in the last few decades can be explained by one or a combination of the following scenarios (Bouchard, 2000). One scenario suggests that a greater percentage of the population is consuming more calories than individuals of past generations, while normal daily energy expenditure has not changed. Another scenario proposes that the increase has occurred through reduced daily energy expenditure and no change in caloric intake. The final scenario suggests that caloric intake per capita has decreased in comparison with past generations, however daily energy expenditure has declined even further. Although each scenario may explain the rise in obesity in certain populations of interest, it appears that the second and third scenario explain the global rise in obesity to an even greater extent. Nutrition surveys over the last few decades in Australia, the Netherlands, and the United Kingdom have reported stable or even decreased caloric intake per capita over time (Bouchard, 2000); the only exception to this is the United States, where data from NHANES I, II, and III revealed a daily increase of 300 kcal per person over the last 15 years (Ernst et al., 1997).

Many studies in the last few decades have illustrated that there is a significant inverse relationship between the level of regular physical activity and weight gain over time (French et al., 1994; Kesaniemi et al., 2001; Prentice and Jebb, 1995). Since lifestyle adaptations over time (such as decreases in physical activity and increases in sedentary behaviour) have been suggested to explain global rises in obesity, there has consequently been growing interest in better understanding the relationship between physical activity and health with the hope of improving the health status of individuals worldwide. In order to adequately examine this relationship, researchers require methods that allow for accurate and reliable assessments of physical activity and energy expenditure. The complexity of physical activity in itself however presents many challenges to those who attempt to measure it.

1.1.2 Definitions of Physical Activity

Physical activity is defined as any bodily movement produced by the contraction of skeletal muscle that substantially increases energy expenditure (Kesaniemi et al., 2001). The amount of energy expended during a particular movement is proportional to the amount of muscle mass involved in that movement. Physical activity is characterized by intensity (rate of energy expenditure), duration of one session, frequency (per hour, per day, etc.) and surrounding environment and social conditions (Montoye, 2000). Furthermore, the type and purpose of physical activity (recreational or obligatory, aerobic or anaerobic, occupational, continuous or intermittent, weight-bearing or non-weight bearing), efficiency of movement and specific energy cost of the activity performed are relevant aspects to consider when quantifying and describing physical activity (Goran, 1998). Ultimately, these measurements provide the means to calculate the dose and/or volume of physical activity, which is one of the potential mediators of the health benefits of physical activity (Kesaniemi et al., 2001). Accurate measurements of both time spent in physical activity and intensity of physical activity are therefore necessary to clarify the dose-response relationship between physical activity and various health-related outcomes.

The amount and type of physical activity can directly influence the development of physical fitness. Physical fitness is characterized by specific traits (such as aerobic power, muscular endurance, muscular strength, body composition and flexibility) that are associated with an individual's ability to perform physical activity (Welk, 2002). Additional fitness characteristics include agility, balance, coordination, reaction time, speed and power (Casperson et al., 1998). Research has demonstrated an inverse relationship between physical fitness and adverse health indicators such as cardiovascular disease risk factors and obesity, noting physical fitness as a critical element of lifelong positive health behaviour (Epstein et al., 2000).

1.1.3 Importance of Physical Activity Measurement

The importance of physical activity in improving or maintaining good health has been established (Kesaniemi et al., 2001). To further examine this relationship, it is critical that physical activity is accurately measured. Accurate measures assist researchers in gaining a greater understanding of the specific amounts of activity that are required to attain health benefits. Furthermore, they allow researchers to better comprehend the mechanisms through which benefits can be attained. Accurate assessments also help investigate theories of physical activity and determine the success of behavioural interventions in altering physical activity behaviour in various populations of interest. Essentially, reliable and valid measurement techniques provide researchers with the tools to effectively study, predict and promote physical activity behaviour (Welk, 2002).

Accurate measurement of physical activity is extremely important when prescribing and monitoring physical activity guidelines for various populations. Recent epidemiological studies have confirmed that moderate levels of physical activity can cause significant improvements in health (Welk, 2002). Previous guidelines, which focused on endorsing more structured, vigorous intensity physical activity, have since been altered to this more appealing behavioural target. Through accurate measurement of physical activity, researchers are able to illustrate the amount of physical activity required to achieve health benefits and therefore increase the chance that target populations will adhere to this prescribed level. Accurate measurement of physical activity is also critical in order to obtain valid statistics on the number of individuals in a population who are meeting guidelines for physical activity.

1.1.4 Physical Activity Guidelines

Physical activity guidelines are primarily established based on research that outlines the health benefits of physical activity. These guidelines have been adapted over time and continue to change as new information is discovered on the relationship between physical activity and health. Specific guidelines exist for different populations of interest (i.e., children, adults, the elderly) and vary internationally. Researchers interested in physical activity measurement help to form these guidelines and also use these as a blueprint for determining the percentage of individuals in a specific population who meet the criteria for adequate habitual physical activity. Table 1.1 presents an overview of current physical activity guidelines.

Table 1.1: Physical activity guidelines for children, youth and adults.

Reference	Country	Frequency	Intensity	Duration
Health Canada Physical Activity Guidelines for Children, 2002	Inactive children and youth in Canada	Daily	Moderate and vigorous	Increase activity by 30 minutes/day in bouts of at least 5-10 minutes Decrease inactivity by 30 minutes/day
Health Canada Physical Activity Guidelines for Children, 2002	Active children and youth in Canada	Daily	Moderate and vigorous	Accumulate at least 90 minutes more activity/day in 5-10 minute bouts Decrease inactivity by at least 90 minutes/day
Health Canada Physical Activity Guidelines for Adults, 1998	Adults in Canada	Daily	Moderate and vigorous	60 minutes; in bouts of at least 10 minutes
American Heart Association, 2005	Children age 2+ in the USA	1. Daily 2. 3-4 days/week	1. Moderate 2. Vigorous	30 minutes; in bouts of at least 10-15 minutes
Centers for Disease Control and Prevention, 1996	Children and youth in the USA	Most days of the week, preferably daily	Moderate	60 minutes
	Adults in the USA	5 or more days/week	Moderate	30 minutes
Healthy People 2010, 2000	Adults in the USA	3 or more days/week	Vigorous	20 minutes or more
Health Education Authority, 2000	Children and youth in the UK	Daily	Moderate	60 minutes
Health Education Authority, 2000	Adults in the UK	5 or more days/week	Moderate	Build up to 30 minutes, bouts of 10-15 minutes

1.1.5 Surveillance Research

Surveillance research concentrates on revealing patterns and trends in physical activity in the population and assessing the changes in these over time (Booth, 2000). It also focuses on monitoring the prevalence and incidence of chronic diseases, conditions and health issues affected by physical activity. Furthermore, surveillance research illustrates the prevalence of behavioural determinants of physical activity in a population (Casperson, 1989). This research helps to identify target groups within the population to be presented with physical activity interventions. This research also aids in identifying possible demographic factors that predict physical activity patterns in the population.

It is important to gain information about physical activity levels and patterns in the population for a number of reasons. This information enables researchers to make cross-cultural comparisons. For example, researchers can determine whether the prevalence and associated trends in one country are similar or significantly different than another country. If differences do exist, this can assist in identifying various policy and environmental discrepancies between countries that could be contributing to these trends and thus provide guidance for constructing and implementing promotional strategies designed to increase physical activity. In addition, this information can provide evidence for government agencies to provide adequate resources for public health funding and develop new and more effective public health messages and policies designed to influence good health and promote activity in the population (Casperson et al., 1998). For example, the Canadian government is strongly committed to improving the national level of physical activity. Federal, provincial and territorial governments have set a national target to increase physical activity by 10 percentage points in each province and territory by 2010 (United States Department of Health and Human Services, 2000). Physical activity surveillance also aids in highlighting the segments of the population most at risk for physical inactivity and associated health consequences. As a result, promotional strategies as well as policy and environmental adaptations can be tailored towards improving the physical activity status of these target groups.

One of the most important goals of surveillance research is to select an instrument that will allow researchers to document trends in physical activity behaviour over the long term. Maintaining a consistent measurement instrument over time is essential for making direct comparisons between studies and allowing reliable and valid comparisons of longitudinal trends in physical activity in a population. Surveillance research also requires a measurement tool that can be administered in an efficient and timely fashion to a large population (Welk, 2002). Consequently, previous surveillance research has relied predominantly on either self-report or interviews for collecting physical activity data. Unfortunately, this information is often subjective and can present difficulties making longitudinal comparisons when changes are made in the measurement tool over time (i.e. wording of questions and/or addition/elimination of questions over time). Ultimately, this hinders the collection of accurate and valid trends in current physical activity levels and trends over time.

Current research suggests that multiple assessment devices may be more useful in obtaining an accurate report of physical activity. For example, Freedson and Miller (2000) suggest that the combination of heart rate data and motion sensor data provides a more detailed representation of physical activity. Additionally, Bassett (2000) has proposed using accelerometers in combination with questionnaires, multiple motion sensors or heart rate and motion sensors. Some surveillance research may be best achieved by selecting multiple measurement tools that facilitate the collection of robust physical activity measures.

1.1.6 Measurement Issues in Specific Populations

The selection of appropriate physical activity measurement tools varies according to the population of interest. Depending on the device that is chosen, researchers may either obtain an accurate and valid portrait of physical activity, or find that the level of physical activity in that population is actually an under-representation or over-representation of the true value. The following are special groups of consideration for physical activity measurement.

1.1.6.1 Women

Measurement of free-living physical activity in women presents specific challenges to researchers. Women often partake in unstructured physical activities that are intermittent in nature, such as occupational, household, transportation-based or family activities (Ainsworth, 2000). A valid and accurate measurement device designed to assess these activities is essential in order to accurately calculate the percentage of women in society who are meeting prescribed guidelines for physical activity. Objective measurement tools such as motion sensors may provide a more accurate report of physical activity in women than self-report instruments, which tend to focus on organized physical activities (e.g., sport, exercise), which may not be reflective of most women's lives or the lives of certain ethnic minority groups (Ainsworth, 2000). Since many surveillance studies in the past have used self-reports to collect physical activity data [NHANES; National Health Interview Survey (NHIS)] the true physical activity levels of these groups may have been underestimated (Ainsworth, 2000). Research does suggest that the physical activity pattern of most women is ambulatory in nature, and therefore the use of motion sensors for physical activity measurement may be a more suitable choice (Leenders et al., 2000).

1.1.6.2 Children and Youth

The measurement of physical activity in young people can also pose quite a challenge to researchers. Accurate measures of activity are necessary to obtain an accurate representation of the percentage of youth meeting physical activity recommendations. Canada's Physical Activity Guide for Children recommends that inactive children should try to accumulate at least 30 minutes or more physical activity per day and reduce the amount of time spent in non-active activities (i.e., watching television, sitting at the computer) by 30 minutes a day, increasing to 90 minutes over the course of several months (Health Canada, 2002a). A combination of moderate and vigorous intensity activity in periods of at least 5 to 10 minutes each should be integrated into the current lifestyle (Health Canada, 2002b).

Youth tend to accumulate their activity in short bursts of time (i.e., 5-10 minutes or less), thus making their activity highly transitory (Saris, 1986). Bailey and colleagues (1995) suggested that the median duration of low and moderate activities was 6 seconds and 3 seconds for high intensity activities. Approximately 95% of physical activity bouts lasted less than 15 seconds and only 0.1% were more than 1 minute in length. Furthermore, there were no bouts of vigorous physical activity that lasted longer than 10 minutes. Rest intervals, although longer in comparison to physical activity bouts, were less than 4 minutes and 15 seconds 95% of the time. These patterns do not tend to match well with the national recommendations of activity, making it difficult to accurately report the prevalence of children meeting the national activity guidelines. In order to accurately capture the physical activity levels of most children, current physical activity guidelines may be better suited to focusing instead on the volume of physical activity accumulated.

The use of self-report instruments for capturing the true physical activity patterns of children may also be problematic. Researchers have discovered that children consistently overestimate physical activity when using these tools (Pate et al., 1994). Children may also have a difficult time interpreting questions on various self-report questionnaires, making it difficult to accurately report their activity. Heart rate monitoring can also be problematic in children, as the delay in heart rate response to movement may mask physical activity information (Nieman, 1999). In addition, the fitness level of children poses problems with using heart rate monitoring, as fitter children will have a higher stroke volume and therefore a lower heart rate for any given activity (Rowlands et al., 1997).

Since motion sensors can provide objective measures of total body movement, they may present a more accurate and valid picture of physical activity in youth. Triaxial accelerometers such as the RT3 (New Lifestyles, Inc., Kansas City, MO, United States) and omnidirectional accelerometers such as the Actical (Mini Mitter Inc., Bend, OR, United States) are able to assess movement in more than one plane. Since children tend to have a larger range of movement than adults in both free-living and controlled conditions (Eston et al., 1998), these devices may be more suitable measurement tools when assessing physical activity levels in children. For example, adults tend to be more efficient at walking and running on a treadmill than youth (Eston et al., 1998). Consequently, uniaxial devices (i.e., pedometers, uniaxial accelerometers) may be more valid in adults, while omnidirectional or triaxial devices may be the best choice for youth. The time interval that data is collected in is an important consideration when using motion sensors with youth. Since children's activity patterns are short and intermittent, selecting a shorter interval (i.e., 5 seconds, 10 seconds) in which data is captured and reported may present a more detailed portrait of activity behaviour (i.e., low, moderate or vigorous activity). Past and current literature has often recorded physical activity in one-minute intervals when using various motion sensors, however due to the unique physical activity patterns of children, using these longer intervals may actually lead to deflated physical activity counts in this population. Another important consideration for researchers is that these devices cannot assess upper body motion (unless worn on the arm/wrist), and therefore they may miss capturing a large portion of activity for children. Despite these inherent limitations, the literature does indicate that activity monitors may be one of the most useful tools to assess physical activity over an extended period of time in children and youth (Welk et al., 2000b).

1.2 REVIEW OF LITERATURE

1.2.1 Measurement of Physical Activity

Currently, there is no gold standard measure of physical activity, a reality that has hindered the designation of a universally accepted field assessment technique (Lamonte and Ainsworth, 2001). As a result, it is often difficult to make direct comparisons between studies that have utilized different measurement tools in assessments of physical activity. This in itself is an obstacle when attempting to reveal true physical activity levels in a population and compare those levels on an international basis. Booth (2000) presents the obvious implications of this issue. He said:

> The consequence of not having agreed standard measures is that direct comparisons of the results of research projects are, at least, difficult and, at worst, invalid. We fall a long way short of enjoying the full benefits of communicating research results to each other when different measures are employed and the international research effort remains fragmented. The development and widespread adoption of one (or even a small number of related measures) would allow direct comparisons of research findings, regardless of the country in which they were conducted, and would catapult our knowledge, and practice, forward.

A number of different techniques have been used to assess physical activity in a variety of populations, each having certain advantages and disadvantages that require consideration for appropriate selection. One review has identified at least six categories of techniques to assess physical activity in youth and adults, illustrating the various strengths and weaknesses of these techniques with respect to reliability and validity (Kohl et al., 2000). Measures of physical activity can be classified into two distinct categories: subjective measures and objective measures. Subjective measures of physical activity depend upon the ability of participants to recall and/or report their own physical activity. These measures include methods such as questionnaires, physical activity records, interviews, surveys and recall diaries. Researchers also conduct subjective measurement using direct observation, a technique dependent upon the researcher’s ability to observe and measure the behavioural aspects of physical activity (Welk, 2002). Objective measures of physical activity provide concrete data relatively free of participant and/or researcher bias. Over time, the application of these techniques has increased, which has led to increased production of new measurement tools and improvements in existing measurement tools for physical activity research. Specific objective measurement tools that have been used in physical activity research include indirect calorimetry, doubly labeled water, heart rate monitors, pedometers and activity monitors.

1.2.2 Subjective Measures of Physical Activity

1.2.2.1 Self-Report Techniques

In past research, observational epidemiological studies of physical activity and health-related outcomes relied preferentially on various self-report methods such as self-administered questionnaires, interview-administered questionnaires, physical activity records, recall diaries and reports by proxy. There are a number of advantages to these techniques, which help explain their popularity for use. Some of the greatest advantages are that they are inexpensive, can be administered quickly and present low participant burden, therefore allowing data to be collected on a large sample size in an efficient manner (Kohl et al., 2000). Self-report techniques also present the opportunity to capture qualitative and quantitative information. Despite these obvious advantages, these methods do however have crucial limitations. For example, these methods rely on the ability of the participant to recall behaviour information accurately. Research has indicated that certain populations such as children are less likely to make accurate self-report assessments than adults (Going et al., 1999; Sallis, 1991). As a result, the reliability and validity of these instruments can be questioned. Young participants may also misinterpret questions posed to them or may deliberately misrepresent information, creating possible content validity problems (Welk, 2002). In addition, self-report methods do not provide adequate description of the intensity and duration of physical activity (Kohl et al., 2000; Pate, 1993), further preventing the ability to assess patterns and/or bouts of physical activity within a certain day or over several days (Trost et al., 2002). Difficulties also arise when attempting to translate activity information from self-reports to energy expenditure (Goran, 1998). Additional research indicates that these methods generally provide less accurate indications of activity than more objective methods, such as doubly labeled water, heart rate monitoring, pedometers and accelerometers (Janz et al., 1995; Sallis, 1991).

1.2.2.2 Direct Observation Techniques

Direct observation is used to measure the behavioural characteristics of physical activity. The main advantage of this technique is that it enables researchers to accurately describe what is taking place in the physical activity environment, thus generating both qualitative and quantitative information. In addition, since physical activities categories are determined before data collection occurs, specific targeting of physical activity behaviours is possible (Welk, 2002). The most obvious disadvantages of this technique are the time and expenses that are necessary for data collection (Montoye et al., 1996). In order to increase confidence that accurate data is collected, observers must go through considerable training and evaluation before and during data collection. This helps to generate high between-observer and within-observer agreement (Welk, 2002). Another limitation of direct observation is that the presence of the observer may disrupt or change regular physical activity patterns, decreasing the reliability and validity of the data (Welk, 2002). As a result of these factors, direct observation is typically confined to studies that are smaller and conducted in distinct settings over a shorter period of time.

1.2.3 Objective Measures of Physical Activity

1.2.3.1 Doubly Labeled Water

The doubly labeled water (DWL) method has been used to assess total energy expenditure in both laboratory and field conditions (Livingstone et al., 1990; Speakman, 1998), and can provide noninvasive and unobtrusive measurements over extended periods of time (1-3 weeks). This is a technique that can predict energy expenditure by using biological markers that represent the body's rate of metabolism (Shoeller, 1988). Participants ingest water with a known concentration of stable, non-radioactive isotopes of both hydrogen and oxygen. Energy expenditure is assessed by determining the difference in the rate of loss between the two isotopes from the body (i.e., urine, sweat, breath, evaporation). The precision of this technique is dependent upon the sampling period. Montoye and colleagues (1996) suggest that a period of two weeks in adults and six to seven days in children is necessary to maximize accuracy. This technique is advantageous as it is able to provide measures of energy expenditure and body composition over long periods of time for children and adults in a noninvasive nature. Furthermore, there is little risk that it will interfere with an individual's habitual physical activity, which can be a concern with other methods (i.e., direct observation).

The doubly-labeled water technique is considered the gold standard for the assessment of energy expenditure in the field (Montoye et al., 1996). As a result, the technique is often validated under controlled or hospital conditions, where CO_2 production and O_2 intake is monitored. Research indicates that in controlled conditions, the validity of this technique is very good (within ±5%) (Montoye et al., 1996) and presents very accurate (4-7%) estimates of free-living energy expenditure and physical activity energy expenditure in the field (Schoeller, 1988). The technique may however be limited in those with atypical diets, high rates of alcohol consumption and/or those individuals with metabolic disorders (Montoye et al., 1996). This technique is further limited for many research applications due to its relatively high cost, lack of availability of the H^2O^{18} isotope and complex application and analysis procedures (Goran, 1998). Another limitation is that this method can only provide information about total energy expenditure and therefore cannot reveal data for specific time intervals or activities (Montoye et al., 1996; Saris, 1986). Finally, an important disadvantage is that this technique does not distinguish between the duration, frequency or intensity of specific physical activity (Lamonte and Ainsworth, 2001), variables that are critical for assessing the relationship between physical activity and health.

1.2.3.2 Indirect Calorimetry

Indirect calorimetry is a technique that uses respiratory gas analysis to measure energy expenditure. This technique is often used to assess energy expenditure over shorter periods of time. With this procedure, individuals wear a mouthpiece, facemask, or canopy during rest or exercise. Oxygen consumption and carbon dioxide production over specific periods of time are measured and used to calculate energy expenditure. Direct calorimetry is usually utilized for longer measurement periods (i.e., approximately 24 hours or more). In this case, the participant is placed in a thermally isolated metabolic chamber. The heat that this individual dissipates (through evaporation, radiation, conduction and convection) is measured and recorded accurately and precisely (Ainslie and Reilly, 2002). Indirect calorimetry is a very precise method of assessing energy expenditure and is recognized as the gold standard approach in many research designs. This technique is however limited in some studies, as it is invasive and costly. Furthermore, it is not particularly good for simulating true free-living conditions, however newer, portable metabolic systems have been introduced to overcome this limitation and therefore offer great potential for future field-validation studies (King et al., 1999).

1.2.3.3 Motion Sensors

While many technological advances over time have contributed to the reduction in energy expenditure in humans, some have made it possible to better assess physical activity by directly recording movement. Various mechanical and electronic devices have been introduced into the research market, such as heart rate monitors, pedometers, and accelerometers. These devices present researchers with raw data that can then be converted into energy expenditure. These techniques are however based on different principles (i.e. physiological, biomechanical, biochemical) and therefore it is not possible to directly compare the raw data (Welk, 2002). Despite this, these techniques have many distinct advantages that support their ongoing use in physical activity monitoring research today.

1.2.3.4 Heart Rate Monitoring

Heart rate monitoring is a method that is often employed in physical activity research, demonstrating good validity in both laboratory and field settings (Welk, 2002). An individual's heart rate provides a direct indication of the physiological response attributable to physical activity (Armstrong, 1998). The method is based on the linear relationship between oxygen uptake and heart rate, making it very useful in assessing energy expenditure during physical activity. Researchers can program heart rate monitors to collect and record data at certain time intervals, which can then be downloaded to a computer to be processed and analyzed. Since it is possible to collect data at specific time intervals, this method provides researchers with a clear illustration of the intensity, frequency and duration of physical activity.

Benefits of heart rate monitoring include its ease of measurement, its ability to record values over time and its indication of the relative stress on the cardiopulmonary system during physical activity (Welsman and Armstrong, 1992). Heart rate can however be elevated by emotional stress, independent of changes in oxygen uptake, and the recovery of heart rate to resting baseline levels can also lag behind the recovery of oxygen uptake to baseline levels (Saris, 1986). Additionally, an individual's heart rate often undergoes a temporal lag in response to the initiation or cessasion of physical activity (Welk, 2002). It has been noted that it takes approximately two to three minutes for heart rate and VO_2 to increase to a level that represents the activity being performed, and an equal amount of time to decrease to resting levels (Strath et al., 2000).

Another limitation of this technique is that various conditions unrelated to a bout of physical activity can generate increases in heart rate without corresponding increases in VO_2. For example, the amount of active muscle mass and the type of activity (continuous or intermittent) can influence the heart rate-oxygen uptake relationship (Klausen et al., 1985). Other factors such as ambient conditions, body position, fitness status, food and caffeine intake, hydration status, previous activity, muscle groups used, smoking, time of day and the static versus dynamic use of limbs can also skew heart rate data (Livingstone, 1997; Maas et al., 1989; Montoye and Taylor, 1984; Parker et al., 1989). As a result of these individual differences, regression equations should be prepared for each individual in order to establish individual heart rate-oxygen consumption relationships (Strath, 2000). Heart rate data is also only accurate for aerobic activities and therefore may not be the most appropriate measurement method to use in certain physical activity monitoring designs. Finally, researchers may face difficulties in deciding how to most effectively and appropriately analyze heart rate data (Welk et al., 2000b). Despite these limitations, heart rate monitoring can provide objective information regarding the intensity of physical activity in either free-living or controlled environments (Welk, 2002). Furthermore, heart rate monitoring has been utilized to validate alternative objective monitoring devices such as pedometers and accelerometers (Eston et al., 1998; Janz, 1994; Welk and Corbin, 1995), tools that have received considerable attention in recent years in the domain of physical activity monitoring.

1.2.4 Pedometers

Pedometers are a type of motion sensor, used predominantly for quantifying ambulatory activity (i.e., walking). They are most commonly used as a step counter; research suggests that data should be represented as steps since this is the most direct form of pedometer output (Tudor-Locke and Myers, 2001). Pedometers can also provide an indication of the distance walked, by multiplying the number of steps by stride length. Variables such as walking speed, height, age and gender affect stride length (Welk et al., 2000c). Gait analysis research indicates that the average walking speed for healthy men is approximately 3.3 mph or 5.3 kph (Temes, 1994). Research also indicates that the average stride length is approximately 42% of a person's height (Bassett et al., 1996; Welk et al., 2000c). Many of the newer pedometer models on the market can also be used to estimate the total number of calories expended if body weight is given and the energy cost associated with walking is estimated (Freedson and Miller, 2000).

There are a variety of reasons to support why there is such a strong interest in measuring walking and walking-based activities. For one, walking is one of the most popular activities in present day society (Welk, 2002). In addition, walking-based activities represent a substantial portion of physical activity energy expenditure reported on physical activity questionnaires and logs (Ainsworth et al., 1993; Bassett et al., 2000). Walking is also a form of lower intensity physical activity and thus is less threatening to individuals, increasing the chance that more people willing to improve their activity levels will adopt it as a form of daily physical activity. This, combined with the fact that walking can be undertaken without the need for exercise equipment or facilities, makes it an easily accessible mode of activity for most individuals. Research has also indicated that walking provides substantial health benefits; it is the recommended form of exercise for secondary prevention of myocardial infarction unless individuals are able to exercise in a supervised setting (Fletcher, 1997) and reduces the risk of cardiovascular disease and cancer (Hakim et al., 1999; Paffenbarger et al., 1978).

Pedometers can offer distinct advantages over self-report methods as a form of physical activity monitoring. For example, physical activity questionnaires typically ask individuals to recall the distance that they walk on a daily basis (Ainsworth et al., 1993). Individuals may have problems with their perception of distance and therefore provide inaccurate reports of the distance actually walked on a daily basis (Welk, 2002). Research also reflects that it is often more difficult for individuals to accurately recall common, moderate-intensity activities such as walking than structured, vigorous exercise (Richardson et al., 1996; Sallis et al., 1985).

1.2.4.1 Nature of Pedometer Design

Pedometer models are often worn on the belt or waistband, however some models have been designed for the wrist, ankle and shoe. Pedometers that are worn on the waist measure activity by detecting vertical accelerations of the hip that occur during walking (Welk, 2002). When vertical acceleration is detected, the pedometer responds by triggering a horizontal, spring-suspended lever arm to move vertically and a ratchet to rotate in order to count that movement as a step (Freedson and Miller, 2000). This action opens and closes an electrical circuit, allowing the accumulated step counts to be revealed in digital format on the face of the device (Schneider et al., 2004). The small size, low cost and ease of use of commercially available pedometers has added to the popularity of this tool for use in physical activity research.

Research with various pedometer models illustrates their potential for assessing daily physical activity. For example, Sequeira and colleagues (1995) found that the pedometer was able to differentiate between several types of occupational activity in adults, such as sitting, standing and moderate-effort occupational activities. However, these devices were unable to assess the energy cost of static work, such as lifting heavy objects. Consequently, physical activity of this nature is underrepresented when using pedometers to assess the daily physical activity patterns of adults. Children however tend to have a significantly lesser amount of static work contributing to their daily energy expenditure than adults (Eston et al., 1998). Consequently, this limitation does not present much of a concern when utilized in this population. If researchers are primarily concerned with assessing walking, which contributes most to an average individual's daily energy expenditure, then these devices might be most suitable to large-scale population studies as they are inexpensive, reusable and objective (Eston et al., 1998).

Pedometers do present limitations for use in habitual physical activity monitoring. For example, since pedometers cannot store data over a specified time interval, they are unable to provide any temporal information concerning activity patterns (Freedson and Miller, 2000). These devices are also limited by their inability to assess the rate and/or intensity of movement, or differentiate between steps accumulated during walking, running or stair climbing (Welk, 2002). As a result, they are limited in their ability to estimate energy expenditure. Furthermore, the devices are not sensitive to isometric exercise, upper body movement or activity that does not require locomotion (Melanson and Freedson, 1996). Pedometers also assume that for every step, an individual expends a constant amount of energy; the Yamax DW-500 (New Lifestyles, Inc., Kansas City, MO) lists this value as 0.55 cal/kg/step regardless of speed (Bassett, 2000), which is considered an oversimplification (Hatano, 1993). Estimates of energy expenditure may be affected by the impact of the feet on the ground or floor surface (Montoye, 2000) or by mechanical vibration when in a motor vehicle (Welk, 2002). Measurement accuracy also decreases at very slow or very fast walking speeds (Bassett et al., 1996; Washburn et al., 1980).

Recent research conducted with a variety of different pedometer models found that pedometers in general are accurate for counting steps, while less accurate for measuring distance and assessing kilocalories (Crouter et al., 2003). The accuracy of pedometer data can be altered within certain populations, such as the obese (Shepherd et al., 1999) and the validity of pedometer data may be affected in individuals with relatively slow walking speeds (i.e., the frail elderly) and those with gait abnormalities (Hoodless et al., 1994). Devices that measure acceleration at the ankle (i.e., AMP activity monitors; Dynastream Innovations, Cochrane, AB, Canada) may be more suitable for providing accurate measurements of walking in these populations. In light of these findings, it appears that pedometers would be most accurate at providing an assessment of energy expenditure when walking comprises most of the activity being measured.

1.2.4.2 Type of pedometer -The Yamax Digiwalker

A number of different pedometer models have been marketed over time for physical activity surveillance research. The Yamax Digiwalker (Yamax DW-500; New Lifestyles, Inc., Kansas City, MO) has been one of the most popular types of pedometers used for physical activity monitoring (Le Masurier and Tudor-Locke, 2003). Although this model has been recently discontinued, other very similar Yamax models have been tested (i.e. Yamax SW-200 pedometer) and found to be very similar in terms of validity to the original model (Welk, 2002).

1.2.4.3 Reliability of Pedometers

When selecting a tool for physical activity measurement, researchers are extremely interested in assessing the ability of a particular instrument to provide consistent and reliable data over time. Analytical variability and biological variability are two constructs that directly affect the reliability of any physical activity measurement tool (Welk, 2002). Analytical variability is assessed by observing the ability of a device to provide reproducible data under the same experimental condition, while biological variability occurs when the actual level of physical activity varies from one measurement period to another (Welk, 2002). Technical sources of variability have been assessed by shaking a number of pedometer devices on a mechanical oscillator and recording any inconsistencies in data among the devices (Tryon et al., 1991). Additionally, researchers have assessed inter-device reliability by having participants wear two pedometers of the same brand on left and right sides of the body during treadmill and over-ground walking. Bassett and colleagues (1996) reported high inter-device reliability between most pedometer brands during a 3.03 mile (4.88 km) walk. Test-retest procedures of over-ground walking have also shown good reliability (average coefficient of variation (CV) = 2.75%, standard deviation (SD) = 3.89%) within pedometer data (Tryon et al., 1991).

Researchers have indicated that the reliability of pedometer data can be increased by using longer sampling periods (i.e., more than one day). For example, pedometer data that is collected over several days and averaged to produce steps/day can present a more representative illustration of an individual's ambulatory activity (Welk, 2002). Various researchers have proposed optimal sampling periods for physical activity measurement. Gretebeck and Montoye (1992) discovered that 5 to 6 days of pedometer data (including both weekdays and weekends) was required to represent typical physical activity in men (i.e., <5% error). Shronhofer and colleagues

(1997) collected activity data on individuals with pulmonary disease over two 1-week periods, 1 month apart; these researchers discovered a high reliability (intra-class correlation coefficient (ICC) = 0.94) amongst steps/day as expressed by the pedometer devices. Sieminski and colleagues (1997) assessed the physical activity of individuals with peripheral vascular disease throughout two 2-day periods, separated by 1 week; these researchers also discovered a high reliability (ICC = 0.86) amongst steps/day. Seasonal variation in activity patterns is also very important to consider when assessing the ability of pedometers to provide reliable and valid physical activity data. Lee and colleagues (1987) used pedometers to evaluate seasonal variation in physical activity in women. Devices were worn for a seven-day period in the summer and a seven-day period in the winter. Results revealed significant decreases in average walking distance from the summer (1.6 ±1.2 miles/day) to the winter (1.2± 0.8 miles/day).

1.2.4.4 Validity of Pedometers

Numerous studies have assessed the validity of the Yamax pedometer models. Hendelman and colleagues (2000) found that the Yamax Digiwalker displayed a high degree of accuracy counting the number of steps over a wide range (50 to 110 m/min) of walking speeds (Hendelman et al., 2000). A high correlation between steps and both walking speed (r=0.86) and VO_2 (r=0.75) was seen for speeds ranging from 63.2 to 111.2 m/min (Hendelman et al., 2000). The validity of the Yamax DW-500 pedometer in measuring energy expenditure was assessed by Nelson and colleagues (1998) who compared the pedometer data to energy expenditure assessed by indirect calorimetry. These researchers found obvious discrepancies in accuracy at different treadmill walking speeds; the pedometer tended to underestimate energy expenditure by 27% at 2 mph and by 7% at speeds $\geq$ 3.5 mph (Nelson et al., 1998). Since the basic mechanics of treadmill and over-ground locomotion are the same, these findings based on treadmill research can also be applied to over-ground walking (Bassett et al., 1985). As such, this device was capable of providing valid results at walking speeds of 3-4 mph, yet underestimated gross kilocalories at 2 mph and below (Nelson et al., 1998). This is supported by research conducted by Le Masurier and Tudor-Locke (2003), who found that the Yamax pedometer consistently under-recorded steps taken at very slow walking speeds (< 60 m/min). Research by Hendelman and colleagues (2000) does indicate, however, that these speeds are much slower than typical normal walking speeds, and thus would not be an important source of error in studies of free-living activity in most populations.

The validity of the Yamax DW-500 has also been compared to a variety of pedometer models, such as the Freestyle Pacer Pro (Freestyle Inc., Camarillo, CA, United States) Eddie Bauer (Eddie Bauer, Inc., Seattle, WA, United States) L.L. Bean (L.L.Bean, Inc., Freeport, ME, United States) and Accusplit (ACCUSPLIT, Pleasanton, CA, United States) (Bassett et al., 1996). Researchers tested the accuracy of these models over a 3.03 mile (4.88 km) sidewalk course. Significant differences were reported amongst the models ($p<0.05$), with the Yamax, Accusplit and Pacer pedometers measuring the actual distance the closest (Bassett et al., 1996). The same study also looked at the accuracy of these pedometers on different surfaces (i.e., concrete sidewalk versus all-weather track courses) and found that the devices reported similar data for both surfaces (Bassett et al., 1996). The accuracy of pedometer models at various walking speeds has also been tested in controlled conditions. Bassett and colleagues (1996) had participants walk on a motorized treadmill at 54, 67, 80, 94, and 107 m/min. Results indicated that the Yamax DW-500 pedometer was significantly more accurate at measuring distance and number of steps than either the Eddie Bauer or Pacer models. The Yamax model was especially more accurate at slower speeds, which reflects the model's greater sensitivity to vertical acceleration (Bassett et al., 1996). At faster speeds however, distance traveled was underestimated by all three pedometer models, which was actually a result of increased stride length at these speeds and not inaccurate reporting of steps (Bassett et al., 1996).

Since walking only represents one form of physical activity, researchers have also been interested in assessing the ability of pedometers to measure other activities such as occupational tasks, activities of daily living, sports and recreation (Welk, 2002). These studies often incorporate the use of small, portable oxygen uptake systems, devices that have emerged and now exist as the gold standard method for direct measurement of energy expenditure in the field (King et al., 1999; Melanson and Freedson, 1995). In 1998, the International Life Sciences Institute (ILSI) provided funding to assess the validity of motion sensors in field settings (Bassett et al., 2000; Hendelman et al., 2000; Welk et al., 2000a). In one study, participants aged 19 to 74 years performed various tasks within six discrete categories: yard work, housework, occupation, family care, conditioning and recreation (Bassett et al., 2000). All participants wore a Yamax SW-701 pedometer and three accelerometers (Bassett et al., 2000). Portable metabolic systems were utilized to measure oxygen consumption for each task (Bassett et al., 2000). Moderate correlations (r=0.49) were found between pedometer data (represented as steps/minute) and energy expenditure across all activities (Bassett et al., 2000). The pedometer was valid for approximating the energy cost of slow walking (average = 78 m/min) and fast walking (average = 100 m/min), however the energy cost of most other activities was underestimated by an average of 1 metabolic equivalent (MET) (Bassett et al., 2000). Researchers indicated that this was a result of the device's inability to assess arm movements and energy expended during external work such as grade walking, lifting/carrying and/or pushing objects (Bassett et al., 2000).

The concurrent validity of the Yamax pedometer has also been assessed. Laboratory research has indicated strong relationships (r=0.80-0.90) between the Yamax pedometer and various accelerometers, including the CSA model 7164 (Manufacturing Technology, Inc. Health Services, Fort Walton Beach, FL, USA) (Bassett et al., 2000). Researchers have also investigated the concurrent validity of pedometers in assessing physical activity in free-living participants. Leenders and colleagues (2000) selected a group of college-aged females in which to evaluate four different methods of assessing physical activity. All participants were outfitted with one pedometer model (Yamax DW-500) and two accelerometer models (Tritrac R3D - Professional Products, Reining Int., Madison, WI, United States; CSA) (Leenders et al., 2000). They were also required to complete a 7-day physical activity recall (7DPAR) (Leenders et al., 2000). Significant correlations were discovered between steps/day, as recorded by the pedometer, and activity counts from both Tritrac and CSA models (r=0.84 to r=0.93) (Leenders et al., 2000). However, when compared to the 7DPAR, the Tritrac, CSA, and Yamax underestimated energy expenditure by 25, 46, and 48% respectively (Leenders et al., 2000). The researchers theorized that these results might be due to the inability of motion sensors to detect certain types of movement (i.e. upper body activity, graded activity). Research by Eston and colleagues (1998) also supports the use of the Yamax Digiwalker for providing accurate assessments of physical activity in children in both laboratory and field conditions. Pedometer steps and oxygen uptake during treadmill walking were highly correlated (r=0.78), while strong relationships between steps and oxygen uptake (r=0.92) and steps and heart rate (r=0.88) were observed during unregulated play activities (Eston et al., 1998).

1.2.5 Accelerometers

Continual technological advances in physical activity measurement have spurred increased development and utilization of various objective activity monitors for assessing physical activity in free-living conditions. For more than 30 years, human movement has been studied using various accelerometry-based devices, however only in the last 10 years has there been a dramatic increase in the use of accelerometers in physical activity measurement. This can be attributed to ongoing advances in technology, which have allowed these devices to become more sophisticated and precise over time. An accelerometer is a type of motion sensor that measures accelerations and decelerations of movement. Acceleration is the change in velocity over time and is usually expressed in multiples of gravitational force (G=9.8 m/s^2, or 32 ft/s^2) (Welk, 2002). Since acceleration incorporates the rate at which distance is covered, it provides an index of movement. According to Goran (1998), “accelerometry is based on the relationship between muscular force and body acceleration that occurs during discrete physical movements.” Consequently, accelerometers are able to provide more direct, objective and accurate assessments of free-living physical activity. These devices are worn on the body (usually at the hip) in order to measure the rate and magnitude of movement in up to three planes (vertical, mediolateral and anterioposterior). An electronic element embedded within the device measures the acceleration of the body. Every time movement is sensed, the device responds by storing a movement count in a specified time interval (i.e., one second, ten seconds, one minute) called an epoch. The data collected is therefore a series of counts representing the intensity of each specific time interval (Nichols et al., 2000).

There are numerous advantages to using accelerometers for physical activity measurement. For one, by measuring acceleration of the body, they provide an objective indication of body movement. The devices are very easy to operate, can collect minute-by-minute data over expended periods of time (i.e., several weeks) and they are small and unobtrusive for participants (Welk, 2002). They also provide the opportunity to analyze frequency, duration and intensity of exercise. Consequently, these devices can be used to assess the effect of lifestyle interventions on activity energy expenditure and physical activity levels, providing researchers with information necessary to support the implementation of these programs to possibly improve activity levels of Canadians. As a result of these characteristics, accelerometers have become very useful measurement tools in both laboratory and field settings.

Although accelerometers have become an important activity assessment tool, there are a few notable limitations. Previous literature illustrates a tendency for accelerometers to over-predict energy expenditure at higher intensities during treadmill exercise (Balogun et al., 1989; Bray et al., 1994; Nichols et al., 1999; Pambianco et al., 1990) and under-predict energy expenditure during field activities (Bassett et al., 2000;

Welk et al., 2000a). Support for this emanates from earlier research by Montoye and colleagues (1983) with the original Caltrac (Hemokinetics, Madison, WI, United States) accelerometer which revealed that these monitors overestimated energy expenditure for activities with a small force to displacement ratio such as jumping or running and underestimated energy expenditure for activities with a large force to displacement ratio such as stair climbing or knee bends. More recent research supports these findings, further noting the devices' inability to detect any additional energy cost of upper body movement (unless devices are placed on upper limbs), load carriage (static work) or movement on soft or graded surfaces (Bouten et al., 1994; Hendelman et al., 2000; Sherman et al., 1998). Since most lifestyle activities involve considerable upper body movement, which cannot be measured with an activity monitor that is worn on the hip, these devices have limited utility in measuring the energy costs associated with various household activities, such as house cleaning and yard work or recreational activities such as golf (Hendelman et al., 2000).

Accelerometer output can also vary according to the place of attachment to the human body (Yngve et al., 2003). Activity energy expenditure is a function of total body acceleration and the mass of the body displaced (Westerterp, 1999). Consequently, researchers often choose to attach devices as close as possible to the center of mass on a participant to increase the validity of the device. Concern over the comparability of data collected via hip placement or lower back placement has been addressed in the literature. Research has shown that monitor placement (i.e., left or right hip) does not appear to have a significant effect on output from the RT3 accelerometer (Powell et al., 2003), which is consistent with research obtained for the CSA accelerometer (Trost et al., 1998).

Financial costs of various accelerometer models may limit their use in certain research designs (i.e., when assessing a large number of participants in the field over extended periods of time). The literature also notes that there is a lack of field-based equations to accurately estimate energy expenditure from accelerometer data in various populations (Welk, 2002). Accelerometers are often used in field-based research designs that measure the activity of participants over an extended period of time. One limitation is that researchers cannot guarantee that there will be consistent and accurate monitor placement on participants, especially young children, over long, unobserved periods of data collection (Welk, 2002). Research has indicated that participants may also periodically tamper with these devices when worn (Welk, 2002). This can directly reduce the reliability and validity of accelerometer data collected.

1.2.5.1 Reliability of Accelerometers

A number of factors can influence the reliability of a measure, such as certain characteristics of the measure itself, the measurement process, the mode of statistical estimation and the participants being measured (Kohl et al., 2000). In order to help verify the utility of accelerometers for use in the assessment of physical activity and energy expenditure, reliability tests must be performed. The reliability of each motion sensor must be assessed to examine if measures are consistent or repeatable over time. Intra-device reliability assesses the consistency of measurement within a device when a repeated stimulus is applied. Inter-device reliability describes the variation in scores between two or more instruments. This can be tested by wearing two devices of the same model simultaneously at approximately the same location on the body (i.e. hip placement – left versus right). Inter-model variability refers to the variation in output between two different models of motion sensors (i.e. MTI versus RT3).

1.2.5.2 Validity of Accelerometers

Accelerometer devices provide the means to quantify energy expenditure, under the assumption that movement (or acceleration) of the limbs and torso is closely related with whole body energy expenditure (Bassett, 2000; Freedson and Miller, 2000; Haskell et al., 1993). Accelerometers detect changes in activity energy expenditure or total energy expenditure, by converting count scores into energy expenditure though an appropriate equation. Research has illustrated a linear relationship between accelerometer counts and energy expended during physical activities such as walking and running (Bouten et al., 1994; Freedson et al., 1998).

Validation of accelerometers is performed against assessments of energy expenditure measured through expired gas analysis (Westerterp, 1999). This method is referred to as indirect calorimetry. Indirect calorimetry involves measuring gas exchange related to the oxidation of energy substrates, and is the most common method used to validate accelerometers. This method involves breathing through a mouthpiece, mask or hood into a gas analyzer or respiration chamber (Westerterp, 1999). Total energy expenditure (TEE), which is comprised of resting or basal metabolic rate (RMR, BMR), diet induced energy expenditure (DEE) and activity induced energy expenditure (AEE) can then be calculated. Variables such as time of day, food intake pattern and activity pattern can influence estimates of energy expenditure. Consequently, validation studies are extremely cautious in standardizing conditions with respect to food intake and time of day when attempting to determine energy expended through activity. When comparing energy expenditure between individuals, additional factors such as age, height, body mass, body mass index, body fat, fitness level and mechanical efficiency must be considered and controlled. It is important to note however that differences in the accuracy of prediction equations used to calculate energy expenditure, rather than differences in technology among the devices themselves, may be partially responsible for inaccuracies in energy expenditure estimations (Welk et al., 2000b). In order to reduce measurement error, appropriate prediction equations must be selected when attempting to translate count scores from motion sensors into energy expenditure. Therefore, it is essential that population-specific regression equations for each activity monitor are developed in order to maximize their validity for physical activity assessment.

1.2.5.3 Accuracy of accelerometers

Both the reliability and validity of a measurement has direct implications on the accuracy of that measurement. Research with accelerometers attempts to determine how well certain models are able to approximate an individual's true level of physical activity. Accuracy is therefore at the heart of all research, since researchers want to be confident that they have chosen the most appropriate instrument to present them with a true representation of a population's amount/type/pattern of physical activity.

1.2.6 Types of accelerometer models

1.2.6.1 Caltrac accelerometer

One of the first accelerometers to be marketed for research and for use by practitioners was the Caltrac accelerometer (Hemokinetics, Inc., Madison, WI, United

States). It is a uniaxial accelerometer, which means that it measures acceleration in the vertical plane only. The device is worn around the waist, positioned at the hip, in order to detect trunk acceleration. The Caltrac operates through a piezoelectric bender element, which consists of two layers of piezo-ceramic material with a brass center (Freedson and Miller, 2000). When acceleration is detected (by a transducer within the device), the transducer bends, emitting a charge that is proportional to the force of movement (Montoye et al., 1996). An acceleration-deceleration wave is produced, and the area under this wave is summed in order to transmit the final count value (Freedson and Miller, 2000). Previous research has produced high correlations between oxygen consumption and Caltrac counts during walking (Maliszewski et al., 1991; Sallis et al., 1990) and moderate correlations between net activity heart rate and Caltrac counts (Sallis et al., 1990). High inter-device reliability and test-retest reliability has also been documented (Sallis et al., 1990). Several studies have, however, found that the Caltrac device significantly overestimated energy expenditure when compared to indirect calorimetry during treadmill walking (Pambianco et al., 1990) and at all walking and running speeds (Haymes and Byrnes, 1993).

The design of the device itself presents further limitations for its use in physical activity monitoring research. Since the output obtained from this device represents only the total counts accumulated throughout the entire monitoring period, neither activity patterns nor changes in running velocity can be assessed (Freedson and Miller, 2000; Haymes and Byrnes, 1993). Furthermore, the device is uniaxial and therefore limited to assessing vertical acceleration only. The attachment location of the device on the body also restricts its utility, since upper body movement cannot be assessed via a hip attachment. Consequently, it is likely not the most appropriate tool for field-based research of most free-living activities that involve upper body movement (housework, gardening, load carriage). In the years following the production of the Caltrac device, a number of different models of accelerometers have emerged, designed to potentially overcome some of the most notable limitations of the original Caltrac model. The smaller size, greater data storage capacity and ability to measure up to three planes of human movement are just some of the features that have made these newer devices popular tools in physical activity research today.

1.2.6.2 Computer Science and Applications (CSA) accelerometer

The Computer Science and Applications (CSA) accelerometer Model 7164 (see also MTI Actigraph, Manufacturing Technology, Inc., Fort Walton Beach, FL, United States) is the most prominent uniaxial accelerometer in both past and present literature.[1] The MTI device is small (5.1 x 3.8 x 1.5 cm), lightweight (42.6 gm) and records accelerations along the longitudinal axis of the human body within the dynamic range of ±2.13 G (Tryon and Williams, 1996). The MTI device is also designed to filter out accelerations whose frequencies lie outside the range of typical human movement, thus improving the reliability and validity of the device in assessing actual physical activity (Bassett, 2000). The manufacturers propose that the acceptable frequency range is approximately 0.21-2.28 Hz (Tryon and Williams, 1996).

The MTI accelerometer is a valuable tool in physical activity research, since it is able to provide the researcher with information on the total amount of physical activity (volume), along with activity patterns (frequency, intensity and time spent in various

[1] It should be noted that for simplicity, all references to CSA will be referred to as MTI for the purpose of this paper. This simply reflects a change in the company and not the device itself.

intensity categories) by storing movement data continuously for up to 22 days with one-minute epochs (Bassett et al., 2000). When used in field research to assess habitual physical activity over time, the data can enable researchers to determine the time of day when children are most or least active and whether intensity of activity varies throughout the day. The ability of the device to capture physical activity data and store it for later analysis eliminates many problems that are associated with subjective recall on physical activity questionnaires (Bassett et al., 2000). Activity counts can also be translated into energy expenditure through equations and validated using other assessments of energy expenditure, such as indirect calorimetry.

Many researchers have assessed the reliability of the MTI device for physical activity monitoring. Research by Metcalf and coworkers (2002) demonstrated low intra-device variability (less than 2%) and low inter-device variability (less than 5%) between 23 MTI devices across two different speeds (medium = 72 rev/m ±60 rev/m; fast = 120 rev/m±84 rev/m) and four different angles of measurement (0°, 15°, 30° and 45°) on a motorized turntable. Trost and colleagues (1998) also reported high inter-device reliability (r=0.87) among MTI devices across a variety of treadmill speeds (3, 4 and 6 mph) in children. However, inter-device reliability has been shown to be poorer at slow walking speeds than during faster walking speeds (Brage et al., 2003c; Nichols et al., 2000; Trost et al., 1998).

The validity of the MTI as a tool for recording energy expenditure has also been assessed by comparing the activity scores generated with indirect calorimetry. For example, Melanson and Freedson (1996) found that MTI counts were moderately to highly correlated with both energy expenditure (r=0.66-0.82) and relative oxygen consumption (r=0.77-0.89) measured from indirect calorimetry during treadmill walking in adults. Further research by Trost and colleagues (1998) revealed that MTI counts were highly correlated with energy expenditure (r=0.86,0.87), oxygen consumption (r=0.86,0.87), heart rate (r=0.77) and treadmill speed (r=0.9,0.89) during walking and running in controlled laboratory conditions. Field based research studies have indicated strong correlations between MTI counts and oxygen consumption (r=0.85) for unregulated play activities (Eston et al., 1998) and between heart rate and MTI counts (r=0.69) during field activities in children (Janz, 1994). Nonetheless, the MTI is limited by its inability to assess upper body movement (when placed on the hip), graded terrains or load carriage, which may restrict its use in providing energy expenditure data for many typical free-living activities.

Following the development of the MTI device, researchers discussed whether a device that was capable of measuring acceleration in more than one plane of movement might offer any improvement over the limitations of uniaxial devices in assessing energy expenditure (Ayen and Montoye, 1998). The original uniaxial accelerometer (i.e., Caltrac) was positioned in each of the three planes on the body and the outputs were combined (Ayen and Montoye, 1988). Results revealed a small improvement in estimating energy expenditure compared with a uniaxial accelerometer. Consequently, the Tritrac (a tri-axial accelerometer device) was later developed (Montoye, 2000).

1.2.6.3 Tritrac R3D accelerometer

The Tritrac R3D (Professional Products, Reining Int., Madison, WI, United States) was the first to be tested, capable of providing a measure of activity counts in three planes of movement (vertical, anterioposterior and mediolateral). This device could be programmed to detect scores in each separate plane of movement or provide a vector magnitude (all planes combined) over a user-specified time interval (Freedson and Miller, 2000). The Tritrac was a little larger than a pack of cards in size (11.0 x 6.9 x 3.3 cm) and weighed approximately 170 gm (Matthews and Freedson, 1995). The device operated via a 9-V battery and was capable of collecting physical activity at one-minute intervals for up to 14 days. Early research by Bouten and colleagues (1994) with triaxial accelerometers supported the utility of this function, since the axis of movement (vertical, anterioposterior or mediolateral) most likely to predict energy expenditure can in fact vary with respect to the activity being performed.

The literature provides some information concerning the inter-device reliability of this device. For example, Freedson and colleagues (1997) used the device to monitor walking and running in children and adolescents, reporting high inter-unit reliability for walking (r=0.97) and low inter-unit reliability for running (r=0.41). These authors proposed that the shifting of the device during running may have contributed to the lower inter-unit reliability seen during this activity. The device has been successfully validated against energy expenditure measured by indirect calorimetry in a variety of laboratory-based activities (mean r=0.86) and also in field research (r=0.62) (Hendelman et al., 2000; Welk et al., 2000a). Eston and colleagues (1998) found that the Tritrac three dimensional accelerometry method was the single best predictor of scaled oxygen uptake (sVO_2) for a variety of children's typical activities when compared to heart rate and pedometer measures[2]. Additional research indicates that

[2] To account for differences in body size between participants, oxygen consumption was expressed relative to body mass and raised to the power of 0.75 (sVO_2).

Tritrac output correlated with heart rate and self-reports in children (Welk and Corbin, 1995) and adults (Matthews and Freedson, 1995) under free-living conditions.

Research has identified that triaxial accelerometers can predict energy expenditure during low intensity activities with higher accuracy than heart rate (Meijer et al., 1989). Furthermore, when using the vector magnitude of all three axes, energy expenditure of sedentary activities and walking was predicted within an accuracy of approximately 15 percent (Bouten et al., 1994). Researchers have further proposed that a more objective measure of physical activity, such as the Tritrac activity monitor, might be able to overcome the limitations associated with activity recalls, which have been shown to overestimate the time that children are moderately physically active (Craddock et al., 2004). Research has shown however that the Tritrac overestimated time spent in sedentary activities, yet underestimated active time and therefore total energy expenditure in free-living conditions (Chen & Sun, 1997; Matthews and Freedson, 1995). More recent research found that the Tritrac overestimated the energy cost of walking and jogging in the field, while underestimating the energy cost of stair climbing, stationary cycling and arm ergometry, when compared to energy expenditure assessed through portable indirect calorimetry (Campbell et al., 2002).

There does appear to be conflicting evidence as to whether a three dimensional device could detect a greater proportion of free-living activity than a uniaxial monitor (Freedson and Miller, 2000). For example, Welk and Corbin (1995) found similar correlations between the Caltrac and Tritrac when used to monitor activity in a field setting. However, Eston and colleagues (1998) found that the Tritrac was a more accurate predictor of relative oxygen uptake in children than the MTI accelerometer across a variety of activities. This could likely be due to the fact that children's activities are sporadic in nature and involve many movements that are non-vertical (i.e., crawling, climbing) compared to those of their adult counterparts (Welk and Corbin, 1995). Since the large size of the Tritrac (120 x 65 x 22 mm, 168 gm) often limited the device's utility in physical activity measurement (Powell et al., 2003), a newer device, the RT3 accelerometer, was developed.

1.2.6.4 RT3 accelerometer

The RT3 accelerometer (StayHealthy, Inc., Monrovia, CA, United States), a much smaller (71 x 56 x 28 mm, 65.2 gm) and more user-friendly tool, is now the standard triaxial device used in physical activity monitoring (Powell et al., 2003). The RT3 accelerometer is able to collect activity data in one second or one minute epochs and accumulate this data for up to 21 days (Powell and Rowlands, 2004). In order to examine the reliability of the RT3 for physical activity monitoring, Powell and colleagues tested 23 devices along each separate axis across three different frequencies (2.1, 5.1 and 10.2 Hz). These researchers found significant intra- and inter-monitor variability, while showing the anterioposterior plane produced greater counts for a given frequency and amplitude of movement than either the vertical or mediolateral plane. In response to these findings, researchers proceeded to investigate the reliability and inter-monitor variability of the RT3 across a number of typical physical activities, such as resting, walking (4 and 6 km/h), running (8 and 10 km/h) and a repeated sit-to-stand activity (Powell and Rowlands, 2004). Results showed that individual RT3 monitors were reliable across trials, however significant inter-monitor differences within each trial were observed. The study also revealed that the vertical plane (X axis of motion) produced that least variability between monitors and thus was the most reliable. The vertical plane also differentiated between activities quite well, and produced the least variability within each activity. Nonetheless, these devices have been validated against oxygen consumption (sVO_2) across a number of activities (r=0.85). Furthermore, researchers found that correlations between the RT3 and sVO_2 (r=0.87) did not differ from correlations between the Tritrac and sVO_2 (r=0.87), supporting their use in physical activity research (Rowlands et al., 2004).

1.2.6.5 Newer motion sensors (Actical, AMP 331)

Fairly recent technological developments have introduced two other motion sensors to activity assessment: the Actical accelerometer (Mini Mitter Inc., Bend, OR, United States) and the AMP 331 advanced activity monitor (Dynastream Innovations, Cochrane, AB, Canada). The Actical is an omnidirectional accelerometer, which means that it is sensitive to movement in all planes of motion within a range of 0.5 to 3 Hz (Mini Mitter, 2003). The device is most often mounted on the hip, with the arrow on its face pointing vertically, which makes it most sensitive to natural vertical movements of the torso (Mini Mitter, 2003). A sensor within the device detects movement and generates a voltage, which is passed into an analog to digital (A/D) converter to create a digital value. Data capture occurs at 32 Hz with average values per second integrated over user-defined epochs (i.e., one minute). The integrated value is divided by four prior to being outputted, yielding an activity count for each minute.

Actical devices are lightweight (17 gm), small in size (28 mm x 27 mm x 10 mm) and waterproof, and thus provide minimal discomfort to participants when worn on a continuous basis. As a result, these devices can be ideal choices when assessing activity levels and patterns of a population over an extended period of time. The devices have been validated against energy expenditure assessed via a portable metabolic system in both adolescents and adults (Heil and Klippel, 2003; Klippel and Heil, 2003). High correlations between predicted and actual activity energy expenditure for hip placement ($r=0.89$, standard error of estimate (SEE) $\pm$ 0.06) support the use of Actical monitors in assessing energy expenditure in these populations. High inter-device reliability ($r= 0.96$) has been documented, supporting comparison of absolute caloric expenditure calculations recorded from any two Actical devices (Mini Mitter, 2003).

The AMP 331 advanced activity monitor is a type of motion sensor that uses sensors and equations imbedded within the device to count steps taken and calculate distance traveled in a given time period (Armstrong et al., 2004). Other gait details such as walking speed, step length, and cadence (step frequency) can be measured. Furthermore, the device can classify each second of the day into one of three different activity classes (inactive, active, and locomotion). This allows the metabolic equivalents associated with each activity class to be determined. In addition, once resting metabolic rate is estimated (through the Harris-Benedict equation), total energy expenditure can be calculated. The Harris Benedict equation is a formula that uses the factors of height, weight, age, and sex to determine basal metabolic rate (BMR). This makes it more accurate than determining calorie needs based on total body weight alone. The only variable it does not take into consideration is lean body mass. As a result, it is very accurate in all but extremely muscular individuals (i.e., underestimates caloric needs) and those with a very high percentage of body fat (i.e., overestimates caloric needs).

The AMP activity monitor is worn in a sleeve around the ankle, and can monitor activity 24 hours a day for up to 9 days. Sensors inside of the device are capable of detecting movement up to 400 Hz. The accuracy of this device has been tested by the manufacturers during a scripted test protocol (where participants took a prescribed number of steps and stopped for a prescribed length of time) with good results. Overall step count was more than 99% accurate, while distance walked was more than 97% accurate, with a maximum error of 5.5% (Gildenhuys et al., 2003). Given the many features associated with this device, and the high degree of accuracy in measuring human gait, it appears that this device could be a very useful tool for some forms (e.g. walking, running) of physical activity monitoring.

1.2.7 Correlates/Determinants of Physical Activity

Objective measurement tools offer researchers the best methods of identifying physical activity levels and patterns in a population. Objective activity monitors such as pedometers and accelerometers present physical activity data in the form of "steps" or "counts", entities that can then be translated into energy expenditure using data transformation equations. In order to accurately calculate physical activity energy expenditure from the raw data captured by these activity monitors, researchers must take into account the many factors that correlate with and/or influence physical activity across the life span (Welk, 2002). Previous research has identified a number of variables such as age, gender, height, weight, percent body fat, fitness level, etc. that correlate with and therefore help predict physical activity. These variables, and others thought to have some predictive utility, are entered into certain equations in order to determine the amount of variance they are able to account for. The step-wise method allows the researcher to personally select the order of the variables to enter into the predictive equation. The order is selected after considering the predictive utility of each variable and identifying those variables which appear to covary.

1.2.7.1 Leg length, stride length and stride frequency

Over time, researchers have suggested that individual differences in leg length, stride length and stride frequency could contribute to variations in activity data output from motion sensors. Using RT3 accelerometers, Powell and Rowlands (2004) discovered that increases in inter-device variability were seen with increasing intensity/speed. Research by Brage and colleagues (2003a) with MTI accelerometers has also recognized this interesting phenomenon. These researchers tested the intra- and inter-device reliability and validity of the MTI Model 7164 accelerometer in a mechanical setting. Six MTI devices were tested with 17 different frequencies (0.5 – 4 Hz) on 3 radius settings (0.022 - 0.049 m), producing 51 different acceleration settings (0.1 – 19.7 m/sec^2). These researchers discovered that the intra-device reliability was generally good, with a mean coefficient of variation of 4.4%. However, the more extreme values of acceleration (less than 1 m/sec^2 and greater than 16 m/sec^2) generated relatively poorer intra-device reliability. Inter-device reliability tests demonstrated both systematic biases and acceleration-specific differences between the devices.

As a result of these findings, many researchers have questioned the influence of inherent individual characteristics, such as leg length, stride length and stride frequency, on the reliability and validity of accelerometers in assessing energy expenditure. For example, Rowlands and colleagues (2004) discovered significant correlations between RT3 counts and sVO_2 in male children and adults, however counts for any given sVO_2

were higher for boys during treadmill activities than for men (Rowlands et al., 2004). Research by Brage and colleagues (2003a) discovered that the validity of MTI accelerometers, expressed as a linear correlation with average acceleration, was dependent on movement frequency. For example, Brage and colleagues (2003c) examined this phenomenon over both walking (3 to 6 km/h) and running (8 to 20 km/h) in adults in both laboratory and field conditions. Results showed that MTI counts increased linearly ($r^2 = 0.92$, $p < 0.001$) with increasing speed up to 9 km/h, but remained constant at approximately 10,000 counts/minute beyond this speed, thus underestimating relative oxygen consumption at speeds greater than 9 km/h. Later research in children demonstrated similar findings, however leveling off occurred at a lower MTI output (approximately 8,000 counts/minute) due to frequency-based filtering (Brage et al., 2003b). These authors proposed that since MTI devices demonstrate frequency-dependent filtering, increases in step frequency at greater speeds should theoretically have contributed to the leveling off of MTI activity counts.

These findings could have important implications when applying them to research previously conducted in various populations. For example, in research with children, Brage and colleagues (2003b) found that the oxygen cost of running at 10 km/h for 3 minutes was underestimated by approximately 20%. Further research by Trost and colleagues (1998) revealed that the standard error of estimate (SEE) between actual and predicted energy expenditure in children increased with treadmill speed (from 0.66 kcal/min at 3 mph to 1.08 kcal/min at 6 mph), which resulted in lower MTI outputs during running. Additional research using Caltrac accelerometers found differences in activity counts between young and old adults walking at various speeds, which could be explained by differences in stride length and stride frequency (Nichols et al., 1992).

There is some discussion in the literature concerning various limitations of certain accelerometer devices that could be contributing to the leveling-off of activity counts at higher frequencies. For example, Brage and colleagues (2003c) have suggested that this phenomenon might be occurring due to biomechanical differences between walking and running. For example, when running at speeds lower than 11 km/h, the average acceleration of the contact phase of the stride is equal to the average acceleration in the aerial phase, which is always 1 G (Cavagna et al., 1988), still within the dynamic range of the MTI device. However, as speed increases above 11 km/h, the relative duration of the contact phase decreases and the rebound becomes asymmetric. Consequently, in order to restore vertical momentum, the average contact phase acceleration must increase, while contact duration decreases. In theory, the MTI device could reach the upper limit of its dynamic range (±2.13 G), which may explain why leveling-off of counts occurs at higher speeds.

Brage and colleagues (2003c) have also suggested that the inability of the device to measure horizontal acceleration, which predominates at faster speeds, may be contributing to the leveling-off of counts. This theory is supported by validation studies of other accelerometers. For example, researchers discovered that Caltrac output remained constant during treadmill running from 8 to 12.8 km/h (Haymes and Byrnes, 1993). In addition, research by Meijer and colleagues (1991) with a triaxial accelerometer illustrated that this device had the greatest sensitivity in the vertical direction and systematically underestimated running intensity. One study, which used the triaxial Tracmor (TRACMOR, Maastricht University, Maastricht, the Netherlands), revealed that data collected in the anterior-posterior direction was able to predict oxygen consumption better than acceleration along the longitudinal axis (Bouten et al., 1994). In light of these findings, the question arises whether a triaxial device programmed to assess and calculate a sum total of accelerations in all three planes of movement might be able to provide more reliable and valid assessments of energy expenditure than uniaxial devices at higher running speeds.

Since differences in leg length, stride length and stride frequency among individuals do appear to have a significant impact on activity counts generated by various motion sensors, some studies have attempted to examine how these differences could affect energy expenditure. For example, researchers have found that that for any given speed, shorter individuals (smaller stride length) will have a higher stride frequency than taller individuals (larger stride length), however oxygen consumption (independent of body size) will be the same (Eston et al., 1993). Data from Rowlands and colleagues (2004) support this claim, since higher RT3 counts in boys for all locomotor activities did not translate into higher sVO_2 when compared to adult males.

Other findings however indicate that younger children consume more oxygen per kilogram of body mass than older children and adults when walking or running at the same speed (Astrand, 1952; MacDougall et al., 1983). Certain factors such as age, substrate utilization, ventilation and anthropometry have been reported to influence submaximal oxygen consumption (Bar-or, 1983; Ebbeling et al., 1992; Martinez and Haymes, 1992; Rowland, 1996; Rowland and Green, 1988) and therefore must be considered. Differences in the mechanics of walking and running between children and adults can also contribute to variations in oxygen consumption and energy expenditure during physical activity (Schepens et al., 1998).

Since there still appears to be a great deal of controversy concerning the effects of leg length, stride length and stride frequency on accelerometer counts and energy expenditure, it is essential that various accelerometer models be exposed to intra- and inter-device reliability and validity testing in a diverse population, namely individuals who differ in the aforementioned characteristics when performing physical activity. These factors could then be entered into regression equations that help us better predict individual energy expenditure. Knowledge about the variability of measures provided by accelerometers is crucial, since this information will help us better understand how these "black boxes" work and allow us to better employ them in our future research. By comparing a variety of accelerometer devices through an activity testing protocol, we can identify whether certain devices provide more reliable and valid assessments of energy expenditure in certain populations than others. Consequently, this information may help direct future accelerometer purchasing decisions when conducting research with a variety of different populations.

1.3 PILOT RESEARCH OF ACCELEROMETER MODELS

As a starting point for this work, a pilot study (Esliger et al., 2004) was completed to test the intra and inter-device reliability of three accelerometer models (MTI, Actical and RT3). This pilot research was conducted using a hydraulic shaker plate to oscillate (i.e. shake up and down) five of each of the three models (MTI, Actical and RT3) of accelerometers simultaneously using various conditions of frequency and/or acceleration. This preliminary work illustrated that accelerometer reliability decreases as the frequency of movement increases at a given acceleration, which corresponds with the data collected by Brage and colleagues (2003a). The results however depict discrepant trends in the accelerometer output data (i.e., count scores) at given accelerations with changing frequencies of oscillation. For example, when keeping acceleration constant at 0.5 G, increases in frequency were associated with decreasing count scores in the MTI device and increasing count scores in the Actical device. Since research has demonstrated that the frequency of oscillation affects both the reliability and the validity of the accelerometers, it must be controlled for, or accounted for, when these instruments are used in practical settings. Therefore, the purpose of this research is to determine the possible influence of varied frequencies of oscillation of one's center of gravity on accelerometer counts and energy expenditure.

1.4 STATEMENT OF THE PROBLEM

1.4.1 Purpose

The primary objective of this study is to assess the influence of leg length, stride length and stride frequency on accelerometer counts and energy expenditure using four accelerometer models (MTI, Actical, RT3 and AMP 331) and one pedometer model (Yamax Digiwalker). This study simply replaces the shaker plate (from previous section) with human participants walking and/or jogging on a treadmill in an effort to generate more "real world" conditions. By comparing count scores generated under the various conditions to directly measured energy expenditure, the validity of these devices can be determined. Furthermore, this will help in identifying whether individual differences in stride length and stride frequency influence a device's reliability and validity in assessing energy expenditure amongst a variety of populations after controlling for age, sex and body mass. These results will also help determine the significant factors necessary to account for to obtain a valid measure of a particular individual's energy expenditure when performing physical activity.

1.4.2 Hypotheses

The hypotheses related to the objectives stated above are as follows:

1. *A leveling-off of count scores will occur at lower speeds for individuals with shorter leg lengths and stride lengths (and therefore greater stride frequencies), than individuals with longer legs .*

Individuals with shorter legs will have shorter stride lengths, greater stride frequencies, and therefore a higher frequency of oscillation of their center of gravity at a given speed. Since these devices are measuring accelerations of the body, yet demonstrate frequency-based filtering, it is proposed that differences in leg length, stride length and stride frequency among participants will cause variations in count scores and energy expenditure both within and between devices across all speeds tested. Consequently, the devices themselves may not be rewarding individuals for energy expended at higher speeds (or intensity) of activity. By measuring energy expended through expired gas analysis and comparing values to energy expenditure generated through activity counts, this can help determine the influence that stride length and stride frequency has on each device's ability to provide a valid assessment of physical activity during treadmill walking and running.

2. *The magnitude of the intra- and inter- instrument reliability measures will differ between the four accelerometer models employed.*

Previous research has indicated that intra-device reliability decreases at extreme values of acceleration, which is where step frequency is thought to play an important role. As such, counts between devices of the same model, as well as between different models of motion sensors, will likely vary with respect to differences in step frequency among individuals at a given speed.

3. *Triaxial devices will provide more reliable and valid assessments of activity at greater speeds and therefore greater accelerations and step frequencies.*

The devices that will be tested do differ with respect to their measurement capabilities, as some can only assess acceleration in one plane of motion, while others can provide data in three separate planes. Since research has indicated that the horizontal (anterioposterior) acceleration predominates at faster speeds, it would appear that the triaxial devices might be able to provide more reliable and valid assessments of energy expenditure under these conditions.

1.5 ASSUMPTIONS

1. It was assumed that participants would provide honest answers to all questions in either self-report physical activity tool [i.e., children - The Physical Activity Questionnaire for Older Children (Kowalski et al., 1997); adults – The Healthy Physical Activity Participation Questionnaire (CSEP, 2003)] as well as the Physical Activity Readiness Questionnaire (CSEP, 2003).
2. It was assumed that participants followed the pre-exercise guidelines as stated by the Canadian Society for Exercise Physiology (CSEP, 2004) when participating in indirect assessments of energy expenditure in the laboratory.

3. It was assumed that participants would complete all three 10 minute stages of treadmill activity to the best of their ability.

1.6 DELIMITATIONS

1. The generalizability of the findings may be limited to the population from which participants were selected.

1.7 LIMITATIONS

1. Individual volunteers were encouraged to participate in this study. As a result, the sample was not randomly selected.
2. Participants were selected based on their ability to accomplish treadmill walking and/or running for ten minutes at three different speeds. These speeds were participant selected from a range provided (i.e., 4 to 12 km/hr). This may have biased the sample used in this study.
3. There was a lack of control over the compliance of participants to adhere to the pre-exercise guidelines as stated by the Canadian Society for Exercise Physiology (CSEP, 2004) when participating in indirect assessments of energy expenditure in controlled, laboratory conditions.
4. Incomplete data sets due to device error were experienced periodically and could not be prevented.

CHAPTER TWO: METHODS

2.1 DESIGN

In order to address the primary research questions, a quasi-experimental single sample design with repeated measures was utilized (Thomas and Nelson, 2001). This research project focused on assessing intra-device reliability, inter-device reliability and inter-model reliability in accelerometers through repeated measurements on participants. Additionally, it sought to examine the ability of certain independent variables, such as leg length, stride length and stride frequency, to predict accelerometer counts and energy expenditure.

2.2 ETHICS

Ethics approval for this project was received from the Biomedical Research Ethics Board at the University of Saskatchewan on October 5, 2004 (Appendix A).

2.3 PARTICIPANTS

2.3.1 Determination of sample size

The sample size used in this research design was based upon careful consideration of both statistical power and feasibility. It was important to have a large enough sample to increase the statistical power of all analyses and therefore allow the proposed research questions to be answered effectively. However, both time and funding constraints had to be recognized and evidently did place limitations on the sample size that was chosen. For this study, the alpha level for all statistical tests was set at $p<0.05$. According to Cohen (1969), in the behavioural sciences, beta (ß) should be set at four times the level of alpha, in order to reduce the chance of making a type I error (rejecting a true null hypothesis). Since power is 1-beta (1-0.2), this sets the power at 0.8, which is accepted as an appropriate level in behavioural research (Thomas and Nelson, 2001). Selecting a sample size that would help assess the practical significance of any relationships among independent and dependent variables was also considered. A moderate effect size (ES) of 0.5 (which is consistent with the literature on physical activity measurement), combined with a power level of 0.80, estimated that approximately 65 to 70 participants would be required (Thomas and Nelson, 2001). Using the same effect size, a sample size of approximately 85 to 90 participants would increase power to 0.90 (Thomas and Nelson, 2001).

Eighty-six participants were included in this research design and were tested on three different occasions (i.e., three different treadmill speeds) for a total of ten minutes at each speed. Three minutes of data (i.e., the first two minutes and the final minute) at each speed were eliminated, leaving seven minutes (times three speeds) for all analyses. All participants also wore two devices of the same accelerometer model. Assuming data from these seven minutes were the same, in terms of intra-device, inter-device and inter-model reliability, this produced a sample size of 516 (i.e., 86 x 3 x 2 for intra- and inter-device reliability and 86 x 6 for inter-model reliability). Analyses of reliability or validity based on independent variables such as leg length, stride length or stride frequency, would be performed with a sample size of 86, as these characteristics are individually-based. According to Thomas and Nelson (2001), in this case, statistical power is $\geq$0.90.

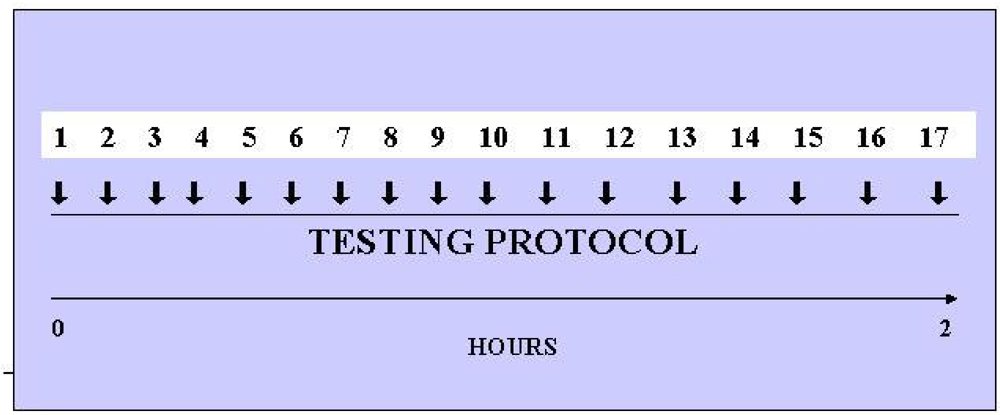
2.3.2 Participants

Healthy male and female participants ranging from 8 to 50 years of age were invited to participate in the study. This population was chosen because it represents much of the growth period, until final completion of growth. Eighty-six participants, age 8 to 40 years (17.6 ± 8.0) from the Saskatoon area volunteered to participate in this study.

2.4 INITIAL DATA COLLECTION

Participants were assessed from October 2004 to May 2005 at the University of Saskatchewan Physical Activity Complex in a Canadian Society for Exercise Physiology accredited laboratory. The participants were recruited from the Saskatoon area using a variety of different tactics. Initially, recruitment posters were placed in and around the University of Saskatchewan Physical Activity Complex to generate interest in the study (Appendix B). An advertisement was later submitted to the Saskatoon Star Phoenix (Appendix C) and posted for two days in order to reach a larger target audience. Two elementary schools in the Saskatoon area, Brunskill Elementary School and John Lake School, were contacted in order to reach the younger population of participants required for this study. The recruitment of these children relied on word of mouth by each school's principal (Appendix D). The recruitment of children also relied on word of mouth by faculty, staff and patrons of the Physical Activity Complex, as well as through various community organizations (i.e. Scouts Canada, Girl Guides Canada, Saskatoon track and field organizations). All participants were offered a small monetary incentive in order to secure their participation and compensate for any travel costs or inconveniences ($10.00).

Since the study assessed the influence of stride length and stride frequency on accelerometer data, it was important to have a fairly representative number of participants across a wide range of heights. An equal number of males and females were grouped into various height categories (4’0 to 4’5; 4’6 to 4’11; 5’0 to 5’5; 5’6 to 5’11; 6’0 to 6’5) for recruitment purposes alone (actual measurements were recorded to the nearest 0.1 cm). It was assumed that if leg length (and thus stride length and stride frequency) were influencing factors, then reliability and validity coefficients between groups would be greater than differences within groups. The sequence for data collection is illustrated in Figure 2.1.



1 = Screening/pre-test guidelines
2 = Anthropometry
3 = Questionnaires
4 = Familiarization to treadmill protocol
5 = Initialization of activity monitors
6 = Attachment of activity monitors
7 = Calibration of metabolic cart
8 = Warm-up and stretching
9 = Attachment to metabolic cart
10 = Speed 1 (10 minutes)
11 = 5 minute rest
12 = Speed 2 (10 minutes)
13 = 5 minute rest
14 = Speed 3 (10 minutes)
15 = 5 minute rest
16 = Cool down and stretching
17 = Explanation of results, questions

Figure 2.1 Temporal sequence for data collection.

Once participants committed to participating in the study, a test time was scheduled for them in the Physical Activity Complex at the University of Saskatchewan. All participants were required to attend both an orientation session and a testing session. These sessions could either be separated into two different appointments (i.e., a 0.5 hour orientation session and a 1.5 hour testing session) or combined into one appointment (i.e., a 2 hour session). All testing was performed by a fully trained Professional Fitness and Lifestyle Consultant (Canadian Society for Exercise Physiology, 2004).

In the orientation session, all participants over the age of 18 were given a consent form (Appendix E), while assent forms (Appendix F) were distributed to all minors (youth age 8 to 18). In addition, Physical Activity Readiness Questionnaires (PAR-Q) were completed by all participants and only those cleared for activity were included in the study (Appendix G). The activity protocol that was utilized in this study involved minimal risk to participants, however, all volunteers were required to complete this medical screening procedure to ensure their safety. Screening cut-offs for resting heart rate (less than 100 for adults and 120 for children) and blood pressure (less than 145/95) were employed prior to exercise testing for all participants (CSEP, 2003). Any questions participants had about the study were answered at this time. In the children's case, a parent's permission (i.e. parent's signature) was required for participation.

2.4.1 Screening Procedures

All testing was performed with one participant at a time. Heart rate was measured in one of two ways. To begin, each participant sat quietly in a chair, both feet placed firmly on the ground in front of them with their left arm extended on the arm of the chair. In one case, resting heart rate (beats/minute) was calculated by taking a 15 second count of the radial pulse and multiplying this number by four. Alternatively, heart rate was calculated using a Polar A1 heart rate monitor and watch (Polar Electro Inc.: Port Washington, New York, United States).

Resting blood pressure was measured with the participant's left arm positioned at a 10 to 45 degree angle relative to their trunk with their palm facing upwards. Next, a blood pressure cuff was wrapped around the upper arm. The radial pressure of each participant was initially taken in order to provide an estimation of each participant's true blood pressure. The brachial artery was then located by palpating the antecubital space. An Almedic AL 10-1800 stethoscope (Almedic: St. Laurent, Québec, Canada) was placed over the brachial artery and the cuff was inflated 20 to 30 mm Hg above the estimated radial pressure. Pressure was released at a rate of approximately two to three mmHg/second. Systolic and diastolic blood pressure were indicated by the first and fourth Korotkoff sounds respectively and recorded from the sphygmomanometer. In order to reduce the chance of anxiety-influenced inflated blood pressure recordings, each participant was familiarized with the procedure prior to the actual measurement.

2.4.2 Anthropometry

Each participant was measured for both standing and sitting height to enable participants to be categorized into groups according to leg length parameters. Standing height was assessed using a stadiometer. Each participant wore light athletic clothing and was measured without footwear. Each participant was instructed to stand with their back erect against the wall, hands hanging parallel to their trunk, feet together, heels touching the back of the wall. The participant was then asked to stand as tall as possible and stare directly ahead while taking a deep breath in. Slight traction was applied to the participant's neck in order to attain their true standing height. Standing height was measured to the nearest 0.1 cm. In order to measure sitting height, each participant sat on a box with his/her feet flat on the ground, back erect and directly against the stadiometer. Leg length was calculated as the difference between standing and sitting heights after taking into consideration the height of the box.

Body mass was measured using a balance beam scale (Toledo: Mettler Toledo, Inc., Canada) and recorded to the nearest 0.1 kg. Each participant was instructed to stand erect in the middle of the scale, still in light clothing and without footwear. Body mass index (BMI) was expressed as body mass (kg) divided by height (m^2). The waist circumference of each participant was calculated using an anthropometric measuring tape (Lufkin Executive Thinline: Lufkin, Inc.), which was placed around the narrowest region of that individual's waist after a normal expiration. Waist circumference was recorded to the nearest 0.5 cm.

Five different skinfold sites (triceps, biceps, subscapular, iliac crest and medial calf) were measured and presented as the sum of five skinfolds for future analyses according to standardized procedures (Canadian Society for Exercise Physiology, 2003). All measurements were taken on the right side of the body. Harpenden C136 skinfold calipers (British Indicators: West Sussex, England) were utilized for all skinfold measurements, which were recorded to the nearest 0.2 mm. For both tricep and bicep skinfold measurements, each participant was instructed to stand erect with his/her arm bent at a 90 degree angle, palm facing up. The tip of the acromion process (right shoulder) and the tip of the olecrannon process (right elbow) were then located and marked. The triceps skinfold was measured (vertical fold) midway between these points on the posterior part of the upper arm, while the biceps skinfold was measured (vertical fold) on the anterior part of the upper arm parallel to this point. The subscapular skinfold was measured 1 centimeter directly beneath the inferior angle of the scapula on a downward and outward angle approximately 45 degrees to the spine. Each participant stood with shoulders relaxed and their arms by their sides while this site was measured. The iliac crest skinfold was measured approximately 3 centimeters above the iliac crest at the mid-axillary line and taken on a forward and downward angle towards the midline of the body. For this measurement, each participant stood in a normal erect position with his/her right arm raised to the side, right hand placed on his/her right shoulder. For the final skinfold measurement, the medial calf skinfold, each participant was instructed to place their right foot flat on a step with their knee bent at 90 degrees. The medial calf skinfold was measured on the medial aspect of the right calf at the greatest area of circumference, with the fold running vertically along the midline. In order to increase accuracy and reliability of results, these measurements were repeated; if these measurements differed by more than 0.4 mm then a third measure was taken. The mean of the two closest measurements was then calculated and recorded for future analyses.

2.4.3 Physical Activity Self Report Questionnaires

Participants were asked to complete a physical activity questionnaire, designed to assess their level of habitual physical activity. The Physical Activity Questionnaire for Older children (PAQ-C) (Kowalski et al., 1997) was given to children, while the

Healthy Physical Activity Participation Questionnaire (CSEP, 2003) was given to adults.

2.4.3.1 The Physical Activity Questionnaire for Older Children (PAQ-C)

The Physical Activity Participation Questionnaire for Older children is used to assess general levels of physical activity during the school year for children in grades four and higher (Crocker et al., 1997). It is a guided self-administered recall questionnaire, which contains 10 questions that ask the participant to recall physical activities during the last seven days (Appendix H). Each participant is assigned a score from 0 to 4; higher scores reflect greater physical activity participation. Previous research indicates that it can provide reliable and valid assessments of physical activity, since it has been significantly and moderately related with other self-administered activity measures (Simons-Morton et al., 1990) and an interview administered activity recall (Sallis et al., 1993). Furthermore, this questionnaire has been successfully validated against activity monitors (Kowalski et al., 1997).

2.4.3.2 The Healthy Physical Activity Participation Questionnaire

The Healthy Physical Activity Participation Questionnaire is a self-administered questionnaire that appears in the Canadian Physical Activity, Fitness and Lifestyle Appraisal Manual (Canadian Society for Exercise Physiology, 2003) (Appendix I). It presents three questions assessing three different aspects of participation (frequency, intensity and perceived fitness). An individual's total score can be used to identify their health status with respect to physical activity participation. This total score ranges from 0 – 11; higher scores indicate better health status in relation to physical activity participation.

2.4.4 Pre-Testing Procedure

After the initial screening procedures and anthropometric measurements were completed, each participant was familiarized with the testing procedure. The primary researcher, a professionally trained Fitness and Lifestyle Consultant, demonstrated proper treadmill exercise technique (walking and jogging) to each participant before allowing them to practice on the treadmill (RunRace 1400Hc; Technogym: Gambettola, Italy). During this time, three treadmill speeds were chosen for the participant to be used in the testing session of the study. These speeds were participant selected, generated from a range of speeds (4 km/hr to 12 km/hr) presented to them to choose from. Speeds were adapted according to the age and physical capacity of all participants. The participant was encouraged to first select a slow, comfortable walking speed (speed 1; range = 4 to 6 km/h), followed by either a quicker walking speed or slow jogging speed (speed 2; range = 5 to 10 km/h) and finally a fast running speed (speed 3; range = 7 to 12 km/h). Each participant was then fitted with the testing apparatus designed to measure oxygen consumption during exercise (head piece, breathing valve, nose clip, etc. - explained in detail in following paragraph) (see Figure 2.6), allowing participants to become knowledgeable and comfortable with all aspects of the testing procedure. This gave participants the chance to ask any questions they might have concerning the study. A time for the testing session was then determined for the participant. If they chose to complete the testing session immediately following the orientation session, resting heart rate and blood pressure were measured in order to ensure that they were safe to participate. If cleared for activity, the participant was fitted with a Polar telemetric heart rate monitor designed to monitor exercise heart rate.

2.5 PHYSICAL ACTIVITY ASSESSMENT

2.5.1 Respiratory Gas Analysis

Respiratory gas analysis is recognized as the gold standard method of measuring energy expenditure during treadmill activity (Welk, 2002). A metabolic cart designed to assess the proportion of inspired and expired gases during treadmill activity was used. Gas analysis was accomplished by drawing samples from a mixing box in the expired gas stream and then measuring volumes at specific intervals by a gas meter connected at the end of the expired gas stream (CSEP, 2004). Ventilation was measured using electronic on-line methods and displayed within a computer software program. Participants were outfitted with a headpiece that was used to attach a breathing valve. Room air was inhaled through the valve and air that was exhaled went through a tube into a metabolic measurement cart. The cart measured the amount of oxygen and carbon dioxide in the exhaled air, as well as the volume of air. Knowing that room air contains 20.93% oxygen and 0.03% carbon dioxide, the amount of oxygen consumed was computed after correction for barometric pressure, humidity and temperature (CSEP, 2004).

Research indicates that these systems provide a convenient and accurate means of assessing energy expenditure during treadmill activity, with rapid calculation and display of results (CSEP, 2004). One important characteristic of this method is that it is only accurate during steady state conditions, as it assumes a proportional match between the analyzed gas samples from the mixing box to the ventilation measured over specific time intervals (i.e., typically one minute) (CSEP, 2004). Steady state occurs when the cardiorespiratory system is able to meet the metabolic demands of the body, which is indicated by a plateau in specific cardiorespiratory variables (e.g., heart rate, VO_2) (Plowman and Smith, 1997). At the onset of short-term, submaximal, light to moderate intensity exercise, cardiac output increases rapidly and plateaus within the first 2 minutes; this demonstrates that the cardiac output is sufficient enough to deliver the oxygen necessary to support the metabolic demands of the activity being performed (Plowman and Smith, 1997). Consequently, it seems reasonable that energy expenditure data should only be assessed after steady state is reached during treadmill activity in order to obtain reliable and valid information.

2.5.2 Activity Monitors

2.5.2.1 Actical Activity Monitor (Mini Mitter Inc., Bend, OR, United States)

The Actical is an omnidirectional accelerometer, which means that it is sensitive to movement in all planes of motion within a range of 0.5 to 3 Hz (Mini Mitter, 2003). The device is most often secured to the hip, with the arrow on its face pointing vertically, making it most sensitive to normal vertical movements of the torso (Mini Mitter, 2003). A sensor embedded within the device detects movement and then generates a voltage, which is passed into an analog to digital (A/D) converter to create a digital value. Data capture occurs at 32 Hz with average values per second integrated over user-defined epochs (i.e., one minute). The integrated value is divided by four prior to being outputted, yielding an activity count for each minute.

Actical devices are lightweight (17 gm), small in size (28 mm x 27 mm x 10 mm) and waterproof, obvious advantages when compared to many of the larger and more cumbersome activity monitors used in past and present research. As a result, Actical monitors provide minimal discomfort to participants when worn on a continuous basis. Inter-device reliability has been assessed on the Actical model and good results have been reported (Mini Mitter, 2003). The devices have also been validated against energy expenditure in both adolescents and adults (Heil and Klippel, 2003; Klippel and Heil, 2003).

2.5.2.2 AMP Activity Monitor (Dynastream Innovations, Cochrane, AB, Canada)

The AMP 331 advanced activity monitor is one of the newer activity monitors on the market today. It is capable of monitoring activity 24 hours a day for a maximum of 9 days. The device is worn around the ankle in a protective sleeve to keep it secured to the ankle during activity. It assesses movement at the ankle by capturing the number of heel strikes an individual performs during any given activity. Sensors and algorithms embedded within the device count steps taken and calculate distance traveled over time (Armstrong et al., 2004). Sensors inside of the device are capable of detecting movement up to 400 Hz. Other gait characteristics such as walking speed, step length, and cadence (step frequency) can be assessed. Furthermore, the device is able to calculate the total amount/percentage of time an individual is inactive and active each day by classifying each second of the day into one of three different activity classes (inactive, active, and locomotion). As such, the caloric expenditure associated with each activity class can be determined. By estimating resting metabolic rate, total energy expenditure can also be calculated. The accuracy of this device has been tested by the manufacturers, who report good overall results (Gildenhuys et al., 2003).

2.5.2.3 MTI 7164 Actigraph (Manufacturing Technology, Inc., Fort Walton Beach, FL, United States)

The MTI 7164 Actigraph is a motion sensor that assesses quantity and intensity of movement by measuring and recording uniaxial accelerations of the body within a dynamic range of ± 2.13 G (Tryon and Williams, 1996). Movement is typically assessed along the longitudinal axis of the human body (Brage et al., 2003b). Piezoelectric bender elements embedded within the device measure the intensity of body accelerations (Brage et al., 2003c). When movement is sensed, the device responds by emitting a voltage signal proportional to the intensity of the acceleration (Brage et al., 2003a). These devices also contain an analogue filter, which allows accelerations outside of the range of typical human movement to be reduced in amplitude (Brage et al., 2003b). The manufacturers propose that the appropriate frequency range is approximately 0.21-2.28 Hz (Tryon and Williams, 1996). Research indicates that human generated accelerations range from approximately 0-60 m/s^2 with a frequency response usually less than 10 Hz (Welk, 2002). Measurements are completed 10 times a second and summed over a specific period of time for data storage (Brage et al., 2003a). Users are able to select the interval length (i.e., epoch), which can range from one second to several minutes or more. Raw acceleration data is then expressed as activity counts over these user-defined intervals. Typically, researchers choose to select an epoch length of one minute, with each minute of data collection representing a stored activity count. The newest MTI devices are small (5.1 x 3.8 x 1.5 cm), lightweight (42.6 gm) and housed in a hard shell, waterproof case and equipped with an infrared computer interface (Welk, 2002). They contain 64 k of memory, which allows data to be recorded for 22 continuous days at 1-minute intervals (Welk, 2002). Research with the MTI Actigraph has reported good reliability and validity for physical activity measurement.

2.5.2.4 RT3 Activity Monitor (StayHealthy, Inc., Monrovia, CA, United States)

The RT3 accelerometer is a much smaller (71 x 56 x 28 mm, 65.2 gm) and more user-friendly device than its predecessor, the Tritrac R3D accelerometer. It is now the standard triaxial model used in physical activity monitoring (Powell et al., 2003). The RT3 accelerometer can collect activity data in one second or one-minute epochs, accumulating and storing this data for a maximum period of 21 days (Powell and Rowlands, 2004). Research with the RT3 activity monitor has demonstrated good reliability and validity for use in physical activity measurement.

2.5.2.5 Yamax Digiwalker (New Lifestyles, Inc., Kansas City, MO, United States)

The Yamax Digiwalker (Yamax DW-500) is one of the newer and more frequently utilized pedometers for physical activity monitoring. This pedometer is relatively inexpensive and has a battery life of approximately three years. The device is worn on the waist and records physical activity by detecting vertical accelerations of the hip that occur during locomotion (Welk, 2002). When vertical acceleration is detected, the pedometer reacts by triggering a horizontal, spring-suspended lever arm to move vertically and a ratchet to rotate to successfully count that movement as a step (Freedson & Miller, 2000). This action opens and closes an electrical circuit and the accumulated step count is revealed digitally on the face of the device (Schneider et al., 2004). Research on the reliability and validity of these devices supports their use as accurate measurement tools for specific types of physical activity (i.e., primarily walking).

An illustration of all five devices is presented below in Figure 2.2.

Figure 2.2 Illustration of (from left to right) MTI Actigraph, Actical, RT3, AMP and Yamax activity monitors (photo: Michelle Stone).

2.5.3 Calibration of activity monitors

Twenty-five activity monitors in total were available for use in this research study. Prior to use in this study, these monitors were subjected to intra- and inter-instrument reliability testing using a hydraulic shaker plate located within the College of Engineering at the University of Saskatchewan. All monitors were initialized using one-minute epochs at a standard setting and secured in an upright position to the bottom of the shaker plate (see Figure 2.3). Five different trials of varying acceleration and frequency were performed on all devices. All trials were five minutes in duration. The various conditions and reliability results are presented in Table 2.1.

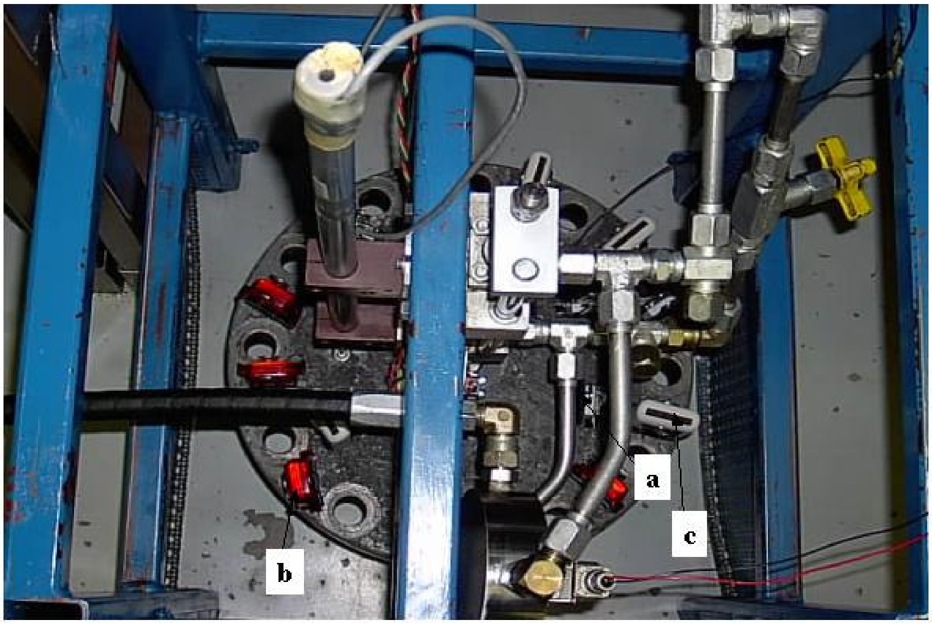


Figure 2.3 Calibration of Actical (a), MTI (b) and RT3 (c) accelerometers using a hydraulic shaker plate.

The displacement capacity of the shaker plate was relatively limited, therefore the range of accelerations was quite low (0.5 – 1.5 G) for all devices. Despite this, intra and inter-device reliability was quite high for all devices, with the exception of the RT3. Reliability (CV%; intra and inter-device) for the Actical was 0.42 and 15.48, 4.09 and 4.94 for the MTI and 46.41 and 42.94 for the RT3 (see Table 2.1). Reliability testing of activity monitors prior to the initiation of the research project enabled the research team to identify any malfunctioning devices or pinpoint any additional problems that could then be solved before actual data collection commenced.

Table 2.1 Intra- and inter-device reliability in accelerometers during shaker plate calibration.

Conditions				Intra-device reliability			Inter-device reliability		
m/s^2	Hz	Model	Counts	SD	SEM	CV	SD	SEM	CV
4.9	1.5	Actical	1960	3.61	1.62	0.19	312.02	139.54	15.92
		MTI	3081	5.20	2.32	0.17	134.85	67.43	4.38
		RT3	584	78.29	35.01	13.22	75.59	33.81	12.72
4.9	2	Actical	2465	27.19	12.16	1.08	492.82	220.40	19.99
		MTI	2668	58.86	26.32	2.19	102.02	51.01	3.81
		RT3	339	333.66	149.22	106.93	317.92	142.18	94.78
4.9	2.5	Actical	2688	7.42	3.32	0.31	536.61	239.98	19.97
		MTI	1877	133.93	59.90	7.13	126.06	63.03	6.72
		RT3	1088	468.83	209.67	43.17	442.43	197.86	42.43
9.81	2	Actical	5003	18.95	8.48	0.36	689.67	308.43	13.78
		MTI	5755	252.35	112.86	4.40	178.10	89.05	3.12
		RT3	2009	772.57	345.50	38.94	699.59	312.87	35.52
9.81	2.5	Actical	6832	23.65	10.57	0.32	1005.31	449.59	14.71
		MTI	5682	63.39	28.35	1.10	222.98	111.49	3.92
		RT3	2242	894.64	400.09	39.97	765.24	342.23	35.30
12.26	2.5	Actical	8275	24.69	11.04	0.29	705.55	315.53	8.53
		MTI	7230	688.24	307.79	9.52	545.90	272.95	7.68
		RT3	3005	1001.40	447.84	36.24	1071.60	479.23	36.92

2.6 TESTING PROCEDURE

All activity monitors (i.e., two of each model – Actical, AMP, MTI, RT3) were initialized using each individual's specific measurement information. The two Yamax pedometers were manually started just prior to treadmill activity. The AMP, Actical, MTI and RT3 devices were initialized using computer software programs developed by the manufacturers of the devices on a Toshiba Satellite 2400-S252 PS240U-02S4H3 PC Notebook (Toshiba of Canada Limited, Markham, Ontario, Canada) containing

Microsoft Windows XP Professional Operating System (Microsoft Canada Co., Mississauga, Ontario, Canada).

The Actical activity monitors were initialized using the following data: identity (i.e., participant code); start date for data collection; start time for data collection; epoch length (i.e., one minute); height (cm); weight (kg); gender; age. Actical monitors were placed on a reader interface unit (i.e., ActiReader) that was connected to the laptop using a RS-232 serial cable (Mini Mitter Co., Inc.: Bend, OR, United States). Initialization instructions were transferred from the ActiReader to the device using a short-range telemetric link. Data was recovered from each Actical device through this process and downloaded using Actical Software (Mini Mitter Co., Inc.: Bend, OR, United States).

The MTI activity monitors were initialized using participant identity, start time, start date and cycle period (i.e., one minute). These devices were also programmed to record steps during treadmill activity. Monitors were placed on a reader interface unit connected to the laptop by a terminal-to-reader interface cable and wall transformer power supply (MTI Health Services Division: Fort Walton Beach, FL, United States). Initialization commands were transported from the reader interface unit to the activity monitor using coded infrared light. Data was retrieved from all MTI devices using the same process and downloaded using ActiSoft Windows Software.

The RT3 activity monitors were initialized with the following data: user ID (i.e., participant code); format (i.e., setting on device = vector magnitude); epoch length (i.e., one minute); height (in); weight (lb); age; gender. RT3 devices were connected to an Activity Recorder Docking Station with a PC interface RJ-11 to DB-9 adapter cable

(Stayhealthy: Monrovia, CA, United States). These devices were manually started (i.e., pressing a start button on the face of the device) just prior to treadmill activity. Data was retrieved from each device using this same process and downloaded using Activity Recorder Software (Stayhealthy: Monrovia, CA, United States).

The AMP activity monitor was initialized using the following data: start date; time; birth date of participant; height (cm); weight (kg); gender; age; epoch length (i.e., one minute). This device was manually started by the researcher (i.e., by pressing a start button on the face of the device) just prior to treadmill activity. Data was collected from this device via a USB AMP link attached to an AMP pod, which provided wireless downloading of the data to the computer. Data was presented using AMP Ware software (Dynastream Innovations Inc.: Cochrane, Alberta, Canada). The initialization set-up for all devices is displayed in Figure 2.4.

Figure 2.4 Initialization set-up procedure for accelerometers (photo: Michelle Stone).

Once all devices were initialized, they were attached to two nylon stretch belts. These devices were then positioned over the left and right hip of the participant (see Figure 2.5). Each participant wore one MTI, one Actical and one RT3 device on the left hip that mirrored a second MTI, Actical and RT3 device on the right hip. Two Yamax pedometers were positioned on the front of the participant's waist, on either side of their umbilicus, using nylon stretch belts. The AMP activity monitors are housed in a sleeve that is worn around the ankle; one device was therefore placed on the left ankle and one device on the right ankle of the participant.

a= Right Actical
b= Right RT3
c= Right MTI
d= Right Yamax

e= Left Yamax
f= Left MTI
g= Left RT3
h= Left Actical

i=Left AMP
j=Right AMP

Figure 2.5 Attachment of activity monitors during treadmill activity protocol (photos: Michelle Stone).

The participant was then asked to perform a treadmill warm-up for three minutes at a self selected walking pace, followed by two minutes of stretching. While the participant was warming up, the metabolic cart was calibrated (Sensormedics MVmax, Series 29; SensorMedics Corporation: Yorba Linda, California, United States). The participant's name, ID code, birth date, gender, height (cm) and weight (kg) were entered into a software program installed on a Sony Trinitron Multiscan 100Sx computer (Sony Electronics Inc.: San Diego, California, United States). The barometric pressure and temperature of the room were also entered. The flow meter (SensorMedics) was then used to draw room air into the metabolic cart as part of the calibration procedure. The gas analyzers were calibrated by drawing a gas mixture of known concentrations through them (i.e., 15-17% O_2 and 3-5% CO_2), concentrations within the physiological range of measurement (CSEP, 2004).

2.6.1 Treadmill Activity Protocol

The participant was fitted with the testing apparatus designed to measure the amount of energy that they would expend by measuring their oxygen consumption during treadmill activity (see Figure 2.6). A form of headgear was placed on each participant, which contained a non-rebreathing valve that the participant held in their mouth. Tape was applied to the participant's nose and a nose clip was used to prevent any breathing through the nose during treadmill activity.

Figure 2.6 Testing apparatus to measure oxygen consumption and energy expenditure during treadmill activity protocol (photo: Michelle Stone).

The participant was then instructed to mount the treadmill in preparation for the test. All instructions were explained to the participant at this time. The tester explained that the participant would begin each treadmill bout at the start of a minute determined by the tester (e.g., 12:00:00) and that the trial would end after ten full minutes (e.g., 12:00:10). The metabolic cart was started at precisely the same time that the participant began their first bout of activity. The participant performed three 10-minute bouts of treadmill activity at the speeds previously selected. The tester recorded the time with a stopwatch that was synchronized with the time expressed on the computer through which all activity monitors were initialized. Time was kept consistent in order to extract data from all methods of activity monitoring using the same three 10-minute segments.

All exercise bouts were separated by a five-minute rest period to minimize any muscle soreness or fatigue. During this time, step counts were recorded from the Yamax pedometers, which were then reset in preparation for the next treadmill speed. By keeping time and velocity constant, and recording the number of steps per minute taken throughout the trial (step frequency – verified by manual counting by the researcher) and the distance covered in each trial (m), the average stride length/step (m) was also measured. Participants also were given a chance to take the mouthpiece out and have a glass of water. Wearing the mouthpiece consistently for the full thirty minutes (plus time in rest) caused the mouth to get extremely dry, therefore the rest period minimized some of the discomfort associated with this apparatus.

Once the last treadmill speed was completed, each participant engaged in a cool down and stretching session. Post exercise heart rate and blood pressure were then taken in order to ensure that the participant was safe to leave the session. The data from the metabolic cart were printed out and explained to all participants and/or their parent(s)/guardian(s). Any questions that either the participant or the participant's parent(s)/guardian(s) had about the session were answered at this time. Finally, all participants were provided with $10.00 as a form of appreciation for their time and effort and to cover any costs incurred while participating in the study (i.e., travel and/or parking fees).

2.7 STATISTICAL ANALYSES

A 3 (models) x 2 (duplicates of each model) x 3 (speeds) x 7 (minutes) repeated measures ANOVA was used to assess intra-device, inter-device and inter-model reliability. Significant effects/interactions were explored using simple effects analysis and a Bonferroni correction for multiple comparisons ($p<0.05$). Data output from each activity monitor (counts/min) was expressed as the mean of 7 minutes on each velocity, leaving out the first two minutes for any speed changes and/or adaptations as the participant approached steady state exercise and the last minute as the participant approached the end of each treadmill bout.

Intra-device reliability was assessed by obtaining coefficients of variation (CV-intra) for each unit. According to previous research, a low CV indicates good reliability (Atkinson and Nevill, 1998). Values of CV-intra were then compared against speed (km/h) and analysed using ANOVA and a Bonferroni correction for multiple comparisons ($p<0.05$) to determine how intra-device reliability varied in the range tested. Inter-device reliability (same models) was assessed by comparing mean differences in accelerometer counts between left and right devices against speed and analyzing these differences using ANOVA and a Bonferroni correction for multiple comparisons ($p<0.05$). In order to assess inter-model variability, mean CV's (CV-intra) for each device (i.e., left and right) of each model were calculated and compared across each speed. Intra-class correlation coefficients of absolute agreement (ICC), a ratio of between-rating variance to total variance, were also calculated, using a two-way random Cronbach's alpha model (Muller and Buttner, 1994).

The relationships among leg length, stride length and stride frequency were confirmed by Pearson product moment correlation coefficients. Counts were plotted against stride frequency and energy expenditure to compare trends between models. Differences between measured and predicted energy expenditure were plotted to illustrate the relationship between these variables. These differences were also assessed across speed categories, using ANOVA and a Bonferroni correction for multiple comparisons ($p<0.05$), to determine the effect of speed on energy expenditure prediction accuracy. Similarly, mean differences were plotted across five height categories and analyzed to determine the influence of leg length on the validity of accelerometer/pedometer data ($p<0.05$).

In order to assess the validity of various motion sensors for physical activity monitoring, the relationship between activity counts and energy expenditure was analyzed using multiple linear regression. Correlations between energy expenditure assessed by respiratory gas analysis and energy expenditure calculated from each activity monitor (i.e., using model-specific manufacturer equations) were presented. Individualized regression equations for each model (i.e., Actical, AMP, MTI, RT3 and Yamax) were developed using mean activity counts/steps generated for each speed, adjusting for various predictor variables (i.e., age, weight, leg length). Comparisons between both methods were made in order to determine whether the addition of certain variables into these regression equations were able to predict more of the variance in energy expenditure.

CHAPTER THREE: RESULTS

3.1 DATA SCREENING

Physical activity, anthropometric and health data were collected on the eighty-six participants involved in this research project. Each participant's data was then examined and any missing or incomplete information was highlighted. The three ten minute bouts (i.e., speeds 1, 2, and 3) of activity data collected from each motion sensor were extracted from the computer-generated software outputs and relocated into personalized excel spreadsheets. The same procedure was performed using energy expenditure data (i.e., VO_2, kilocalories per minute) collected through expired gas analysis. The first two minutes of data at each speed were eliminated in order to account for speed changes or biomechanical adaptations as each participant approached steady state exercise. The last minute of data at each speed was also removed as each participant approached the end of the treadmill bout. As a result, seven minutes of data for each of the three treadmill bouts remained for analyses. Each personalized spreadsheet was analyzed for complete data for the activity monitors (i.e., Actical, AMP, MTI, RT3 and Yamax) and respiratory gas analysis. Incomplete data was defined as any data outputs that contained "0 counts" or alternatively "0 kilocalories" from minute one to minute seven for a given treadmill bout. A count of 0 suggests that the device was not capturing activity information and therefore was in some way malfunctioning during that given monitoring period. Respiratory gas analysis data was complete for every participant (100 % data capture). Incomplete data were however evident among the activity monitors; particularly the AMP models. Those participants with incomplete activity data were excluded from various analyses. For example, if a participant was missing activity data from the left MTI monitor however did have data from the right MTI monitor, they were excluded from inter-device reliability analyses. However, both intra-device and inter-model reliability analyses could be performed on this individual.

Data collected from all participants was then examined in order to locate any outliers. Coefficients of variation within devices (CV intra) were calculated for each device (i.e., AMP, Actical, MTI, RT3) at speeds 1, 2 and 3. Outliers were defined as those cases (i.e., mean of minute 1 to minute 7 at any given speed) that had intra-device variation of greater than 40%. As a result of this criterion, 6 cases were eliminated. Outliers were also defined as those cases in which saturation of activity counts occurred. For both the Actical and the MTI models, there exists a dynamic range in which body acceleration can be sampled. Once the upper limit of this range is reached, saturation will occur. In the Actical, this occurs at 13176 counts per minute. In the MTI, this occurs at 32767 counts per minute. Using this criterion, 69 cases were eliminated (57 from the Actical and 12 from the MTI). Finally, outliers were also defined as those cases in which a participant did not complete the entire seven minutes of a given treadmill bout. Only one participant experienced difficulties successfully completing their last selected treadmill bout, which caused extreme scores to be present in the activity and energy expenditure data sets. As a result, data from this last treadmill bout were eliminated from all analyses.

Participant dropout was not a large concern for this research study, since the design consisted of a one-time only testing period for 2 hours in duration (see Figure 2.1). It should still be noted however that all individuals who consented to participate in this study completed the study and did so to the best of their ability.

These data screening decisions resulted in 44% missing data in AMP devices, 15% missing data in Actical devices, and 10% missing data in MTI devices. In the RT3 devices, less than 1% of data was missing. The Yamax pedometers provided 100% good data.

3.2 DESCRIPTIVE RESULTS

Descriptive statistics (mean ± standard deviation) for age, height, weight, leg length, body mass index, waist circumference and sum of five skinfolds are presented in Table 3.1. In addition, Table 3.1 illustrates mean scores on both physical activity questionnaires (i.e., Healthy Physical Activity Participation Questionnaire, Physical Activity Questionnaire for Older Children) administered in this study. Independent samples t-tests reflect the differences in these variables across gender.

Table 3.1 Descriptive characteristics of study participants (mean ± standard deviation).

VARIABLE	**MALES**	**FEMALES**
Sample size	41	45
Age (yrs)	16.7 ± 8.0	18.4 ± 8.0
Height (cm)	161.8 ± 21.9	159.0 ± 16.7
Weight (kg)	57.6 ± 25.0	54.3 ± 19.3
Leg length (cm)	77.0 ± 10.6	75.6 ± 7.2
Body mass index (kg/m^2)	20.7 ± 4.4	20.7 ± 3.9
Waist circumference (cm)	71.6 ± 13.6	67.5 ± 10.3
Sum of five skinfolds (mm)	*47.2 ± 17.5	62.6 ± 23.4
Healthy PA (score)	9.8 ± 1.9	9.6 ± 2.2
PAQ-C (score)	3.3 ± 0.8	3.1 ± 0.5

*Significant gender difference ($p<0.05$); PA = physical activity

The descriptive results illustrate that there are no statistically significant differences between males and females for age, height, weight, leg length, body mass index, waist circumference and both activity questionnaires (i.e., HPAQ, PAQ-C). As a result, the predictive utility of these variables with respect to accelerometer counts and energy expenditure does not differ by gender and therefore they can be equally applied for both males and females. Table 3.1 does reveal a statistically significant difference in sum of five skinfolds between males and females ($p<0.01$); sum of five skinfolds were, on average, 15.4 ± 5.9 mm greater in female participants. Since the ability of this variable to explain some of the variance in accelerometer counts and energy expenditure differs by gender and correlates with other anthropometric variables (i.e., BMI, R^2 =

0.50; waist circumference, R^2 = 0.33; weight, R^2 = 0.26), its use in predictive models may be limited.

3.3 COMPARISONS OF AGE, WEIGHT, HEIGHT, LEG LENGTH, STRIDE LENGTH AND STRIDE FREQUENCY ACROSS SPEED

In this study, participants were able to choose three individual treadmill speeds from a range provided (i.e., 4 to 12 km/h), to complete each activity bout (i.e., speed 1 = walk, speed 2 = walk/jog, speed 3 = run). It was hypothesized that younger children would choose slower speeds (especially for speed 3), as shorter leg lengths might make it more physically demanding and therefore more difficult to successfully complete faster speeds. Similarly, it was predicted that those with longer leg lengths would choose higher speeds, although fitness level would likely be a strong influencing factor. Despite different choices in speed, it was hypothesized that those individuals with shorter leg lengths walking/running at slower speeds would have comparable stride frequencies to those individuals with longer leg lengths walking/running at faster speeds. Tables 3.2, 3.3, and 3.4 summarize these results.

Table 3.2 Comparisons of age, weight, height, leg length, stride length and stride frequency across speed in speed category 1.

VARIABLE	**4 km/h (1)**	**5 km/h (2)**	**6 km/h (3)**	**Post-Hoc**
N	41	31	14	
Age	13.1 ± 7.0	20.4 ± 7.1	24.2 ± 4.0	2=3; 2>1; 3>1
Weight (kg)	41.2 ± 17.0	65.2 ± 17.7	77.9 ± 13.5	2=3; 2>1; 3>1
Height (cm)	145.5 ± 13.7	170.8 ± 13.0	181.0 ± 9.2	2=3; 2>1; 3>1
Leg length (cm)	69.9 ± 6.7	80.4 ± 6.3	85.4 ± 6.2	2=3; 2>1; 3>1
Stride length (cm)	61.0 ± 4.7	73.9 ± 4.7	85.7 ± 3.4	3>2>1
Stride frequency (steps/min)	109.9 ± 8.7	113.1 ± 7.1	116.8 ± 5.1	1=2; 2=3; 3>1

Table 3.3 Comparisons of age, weight, height, leg length, stride length and stride frequency across speed in speed category 2.

VARIABLE	5 km/h (1)	6 km/h (2)	7 km/h (3)	8 km/h (4)	9 km/h (5)	10 km/h (6)	Post-Hoc
N	18	15	16	15	13	9	
Age	9.0 ± 1.1	14.0 ± 8.0	17.7 ± 6.6	22.7 ± 7.7	23.1 ± 4.7	23.7 ± 3.4	1=2; 2=3; 3=4,5,6; 4 =5,6; 5=6
Weight (kg)	31.9 ± 3.5	44.9 ± 20.3	57.7 ± 22.3	65.7 ± 15.2	73.2 ± 14.2	77.4 ± 10.4	1=2; 2=3; 3=4,5,6; 4=5,6; 5=6
Height (cm)	136.0 ± 6.4	148.6 ± 13.0	162.4 ± 12.1	170.6 ± 13.5	176.7 ± 8.9	184.3 ± 5.9	3=4; 4=5; 5=6
Leg length (cm)	67.4 ± 7.4	70.5 ± 6.1	76.2 ± 4.2	79.6 ± 7.1	82.6 ± 5.3	88.8 ± 3.2	1=2; 2=3; 3=4,5; 4=5; 5=6
Stride length (cm)	65.3 ± 3.7	74.3 ± 5.2	82.1 ± 8.3	85.0 ± 6.3	96.0 ± 4.2	109.2 ± 3.7	3=4
Stride frequency	127.9 ± 7.2	135.2 ± 10.5	143.6 ± 14.8	157.7 ± 11.6	156.5 ± 6.8	152.8 ± 5.1	1=2; 2=3; 3=6; 4=5,6; 5=6

Table 3.4 Comparisons of age, weight, height, leg length, stride length and stride frequency across speed in speed category 3.

VARIABLE	7 km/h (1)	8 km/h (2)	9 km/h (3)	10 km/h (4)	11 km/h (5)	12 km/h (6)	Post-Hoc
N	8	20	16	18	9	15	
Age	8.3 ± 0.7	11.9 ± 6.4	15.3 ± 7.2	22.7 ± 7.2	23.3 ± 5.5	22.7 ± 3.2	1=2,3; 2=3; 4=5,6; 5=6
Weight (kg)	31.3 ± 3.8	40.0 ± 19.3	51.7 ± 22.6	63.8 ± 14.7	71.6 ± 13.1	75.6 ± 13.0	1=2,3; 3=4,5; 4=5,6; 5=6
Height (cm)	132.8 ± 3.7	144.5 ± 13.7	156.5 ± 14.1	167.8 ± 10.6	178.9 ± 10.4	180.2 ± 9.4	1=2; 3=4; 4=5,6; 5=6
Leg length (cm)	63.6 ± 5.9	70.8 ± 6.8	74.3 ± 6.7	77.9 ± 4.7	84.4 ± 5.8	85.5 ± 6.2	1=2; 2=3; 3=4; 4=5; 5=6
Stride length (cm)	65.4 ± 6.3	76.4 ± 4.4	90.8 ± 6.8	103.3 ± 6.2	114.0 ± 8.1	124.8 ± 5.9	6>5>4>3>2>1
Stride frequency	179.8 ± 16.1	175.0 ± 9.5	163.3 ± 19.9	162.7 ± 9.0	161.5 ± 11.2	160.6 ± 8.0	1=2,3,5; 2=3,4,5; 3=4,5,6; 4=5,6; 5=6

The results from Tables 3.2, 3.3, and 3.4 reveal that there are significant differences ($p<0.05$) between age, weight, height, leg length, stride length, and stride frequency across speed within each speed category (i.e., speed 1, 2, and 3).[3] Post-hoc analyses were performed in order to determine where these differences occurred. If the two extreme speeds in each speed category are compared, it appears that participants

[3] Note: If differences between speed are not identified as equal, there are significant differences.

who chose the lowest speed were significantly younger, lighter, shorter, and had shorter legs in comparison to participants who chose the fastest speed, who were significantly older, heavier, taller and had longer legs. In speed category 1, stride length was significantly greatest for the fastest speed (i.e., 6 km/h), however stride frequency was only significantly different between 4 km/hr and 6 km/h. In speed category 2 and 3, it appeared that when looking at both extremes (i.e., 5 km/h and 10 km/h; 7 km/hr and 12 km/h, respectively), those participants at the lowest speeds were significantly younger and lighter, and had shorter leg lengths and stride lengths. When looking at stride frequency however, although stride frequency was much higher for participants walking/jogging at 10 km/h than 5 km/h (i.e., in speed category 2), when participants transitioned into a run, it appeared that those participants running at 7 km/h (height = 132.8 ± 3.7 cm) had significantly higher stride frequencies than those running at 12 km/h (height = 180.2 ± 9.4 cm).

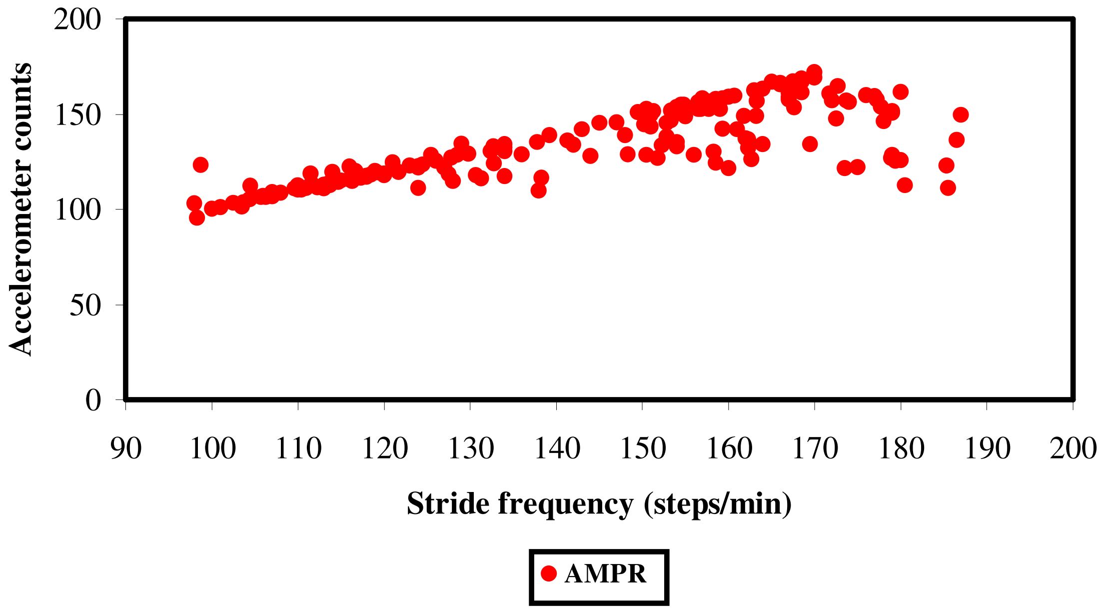
3.4 RELATIONSHP BETWEEN LEG LENGTH, STRIDE LENGTH AND STRIDE FREQUENCY

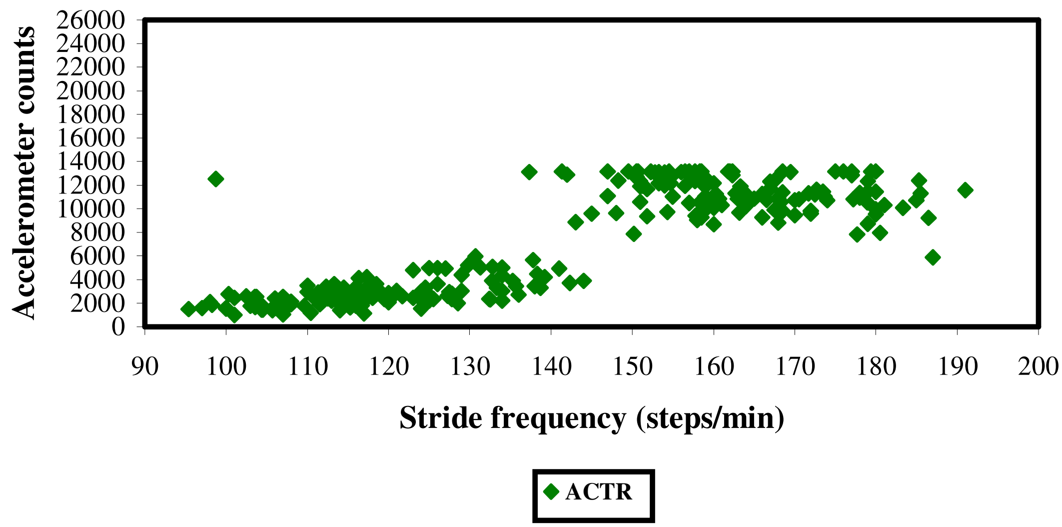
One of the primary hypotheses of this research project was that there would be a significant relationship between leg length, stride length, and stride frequency, and that differences in these characteristics among participants would affect accelerometer counts and the prediction of energy expenditure. Correlations between leg length, stride length and stride frequency at speeds 1 (i.e., walk), 2 (i.e., walk/jog), and 3 (i.e., run) were assessed using Pearson Product Moment correlation coefficients. For speed 1, there were significant correlations between leg length and stride length (R^2 = 0.67, $p<0.01$) and leg length and stride frequency (R^2 = -0.05, $p<0.05$). For speed 2, there were significant correlations between all three variables (i.e., leg length and stride length, R^2 = 0.64; leg length and stride frequency, R^2 = 0.13; stride length and stride frequency, R^2 = 0.12; $p<0.01$). For speed 3, there were also significant correlations between all three variables (i.e., leg length and stride length, R^2 = 0.66; leg length and stride frequency, R^2 = -0.44; stride length and stride frequency, R^2 = -0.42; $p<0.01$). For all three speed categories, there was a positive association between leg length and stride length, however this was not the case for the other variables. It appears that for the first and third speed category, those individuals with shorter leg lengths had higher stride frequencies. For speed category 2, there appears to be a positive association between stride length and stride frequency, however there is a negative relationship between these variables during speed category 3. These results suggest that as participants transitioned into a run, there seemed to be a trade-off between stride length and stride frequency, where either an increase in stride length was associated with a decrease in stride frequency, or a decrease in stride length was related to an increase in stride frequency.

3.5 RELATIONSHIP BETWEEN STRIDE FREQUENCY AND ACCELEROMETER COUNTS

Previous research has illustrated that accelerometer counts increase linearly with increases in speed, however in some models, accelerometer counts begin to level-off when higher speeds are reached (Brage et al., 2003c). Since each accelerometer is capable of detecting and reporting movement within certain ranges of frequencies, it is possible that when plotting accelerometer counts against stride frequency, counts may begin to level-off once high stride frequencies are reached. Figure 3.1 portrays trends in accelerometer counts across stride frequency for right-mounted AMP, Actical, MTI, and RT3 activity monitors.

Throughout the results section, the following nomenclature will be used to distinguish left devices from right devices: left AMP (AMPL), right AMP (AMPR), left Actical (ACTL), right Actical (ACTR), left MTI (MTIL), right MTI (MTIR), left RT3 (RT3L), right RT3 (RT3R), left Yamax (YAMAXL), and right Yamax (YAMAXR).





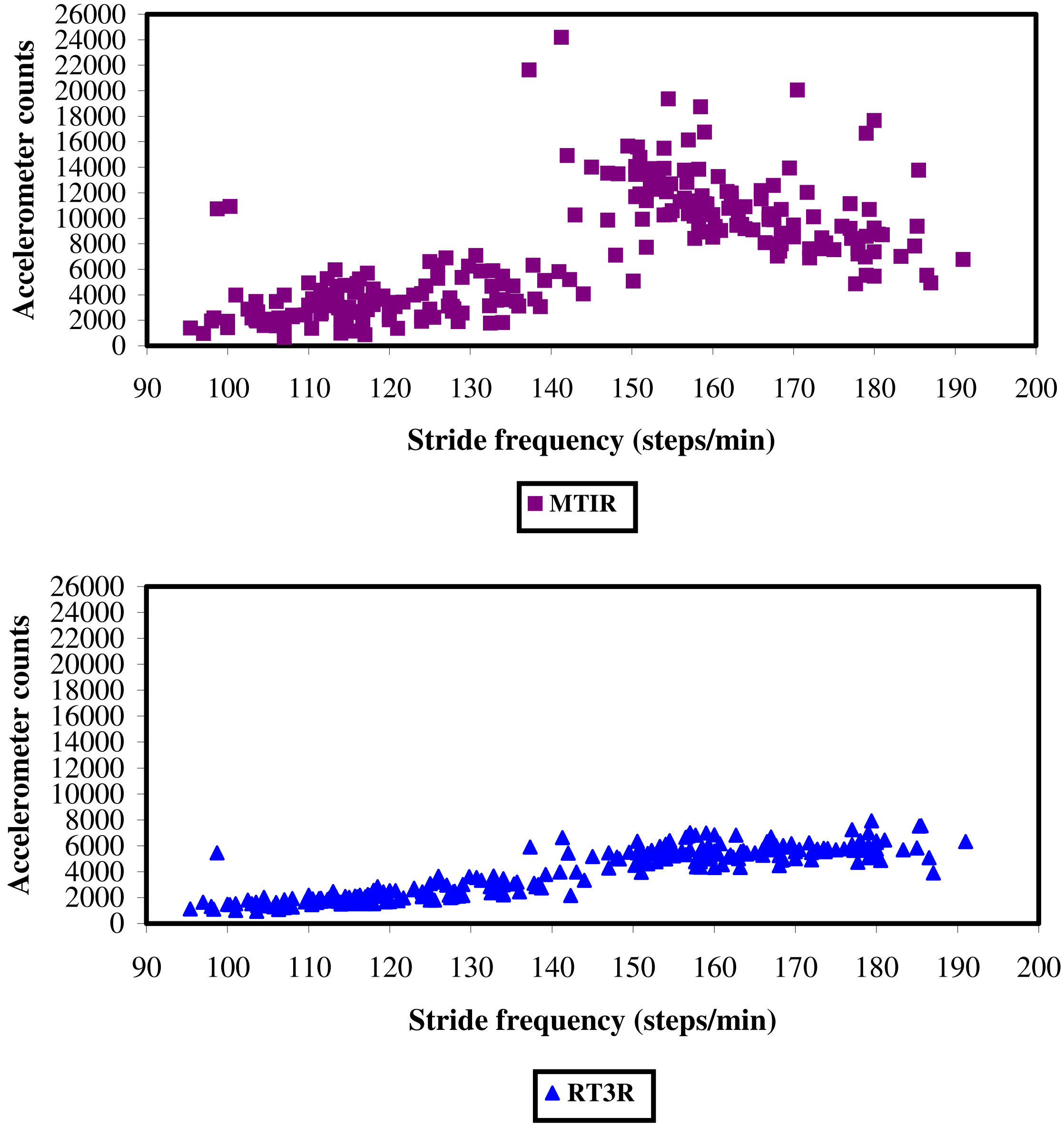


Figure 3.1 Relationship between stride frequency and accelerometer counts in AMP, Actical, MTI and RT3 activity monitors.

Figure 3.1 displays unique trends in accelerometer counts across stride frequency for AMP, Actical, MTI, and RT3 models. In the AMP activity monitor, counts appear to increase linearly with stride frequency (R^2 = 0.55), however beyond

140 steps/min, there is greater variation in accelerometer counts. In the Actical, counts appear to increase linearly as stride frequency increases (R^2 = 0.72), however counts begin to plateau once higher stride frequencies are reached (i.e., between approximately 140 to 150 steps/min). In the MTI model, counts appear to increase linearly with stride frequency (R^2 = 0.42) up until approximately 140 steps/min, after which there is large variation in accelerometer counts. In the RT3 model, there is a strong linear relationship between accelerometer counts and stride frequency (R^2 = 0.81) and this linear relationship appears to be maintained across high stride frequencies. These trends suggest that for many models, a plateau in accelerometer counts occurs once high stride frequencies are reached, which poses the question of whether this plateau effect could directly affect estimates of energy expenditure.

3.6 DIFFERENCES IN ACCELEROMETER COUNTS WITH RESPECT TO SPEED AND MONITOR PLACEMENT

A repeated measures analysis of variance (ANOVA) was used to examine the effects of both speed and monitor placement on accelerometer counts. For this analysis, three models were selected: the Actical, MTI and RT3. The AMP devices were eliminated from this analysis simply because of the high percentage of incomplete data across all speeds. In this design, there were two fixed variables [i.e., model – three levels (Actical, MTI and RT3) and device – two levels (left and right)] and two repeated measures [i.e., minutes – seven levels (minute 1 to 7) and speed – three levels (speeds 1 to 3)]. Significant effects/interactions were explored using simple effects analysis and a Bonferroni correction for multiple comparisons ($p<0.05$). The analysis was conducted on 43 participants. Although data on 86 participants were available, some cases were eliminated due to saturation in Actical and MTI devices.

Results revealed that the assumption of sphericity was not met and therefore the variance among the repeated measures is significantly different ($p<0.01$). As a result, a correction was used to adjust the degrees of freedom. The test of within-subjects effects revealed that there were significant main effects for model, device, speed and minutes on accelerometer counts ($p<0.01$). As a result, differences in accelerometer counts will occur between different models, between left and right devices, across speed and across minutes of recorded data for the same individual. Results also revealed a significant three-way interaction between model, speed and device [$F(1.39, 61.27) = 16.44$, $p<0.01$] and a significant two-way interaction between model and minute [$F(4.21, 185.43) = 2.38$, $p<0.05$]. Since there are interaction effects, the main effects were ignored. It was concluded that a participant's accelerometer counts depended upon the interaction of model used and anatomical positioning across speed, as well as the model used across time recorded.

Profile plots of the estimated marginal means were created in order to look at the interaction of model, device and speed on accelerometer counts, as well as the interaction of minute and speed on accelerometer counts. Results are illustrated in Figures 3.2 and 3.3.

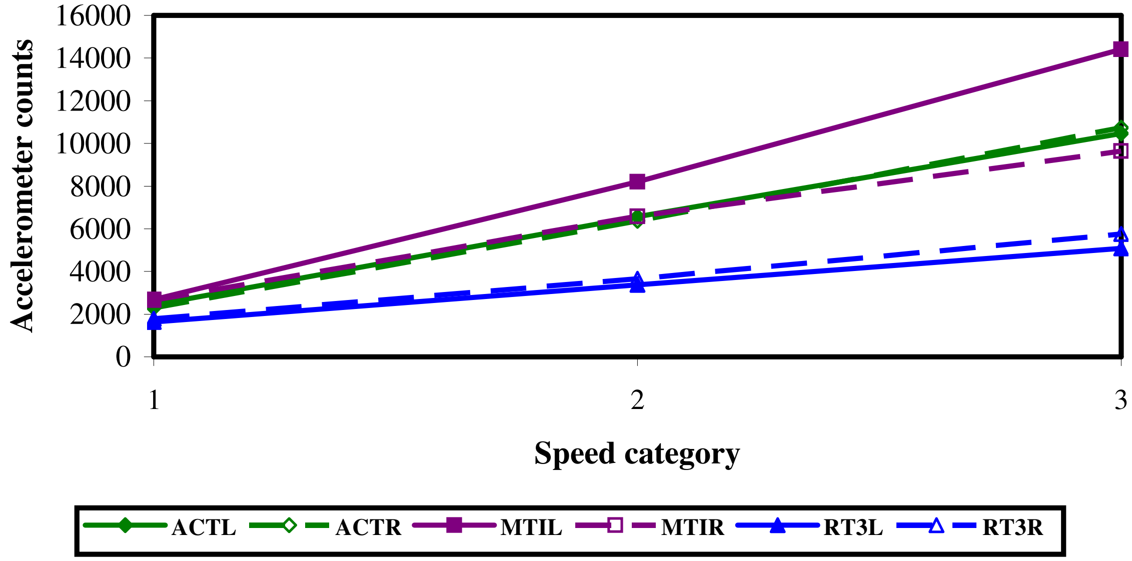


Figure 3.2 Comparison of accelerometer counts across speeds between left and right devices of Actical, MTI, and RT3 monitors.

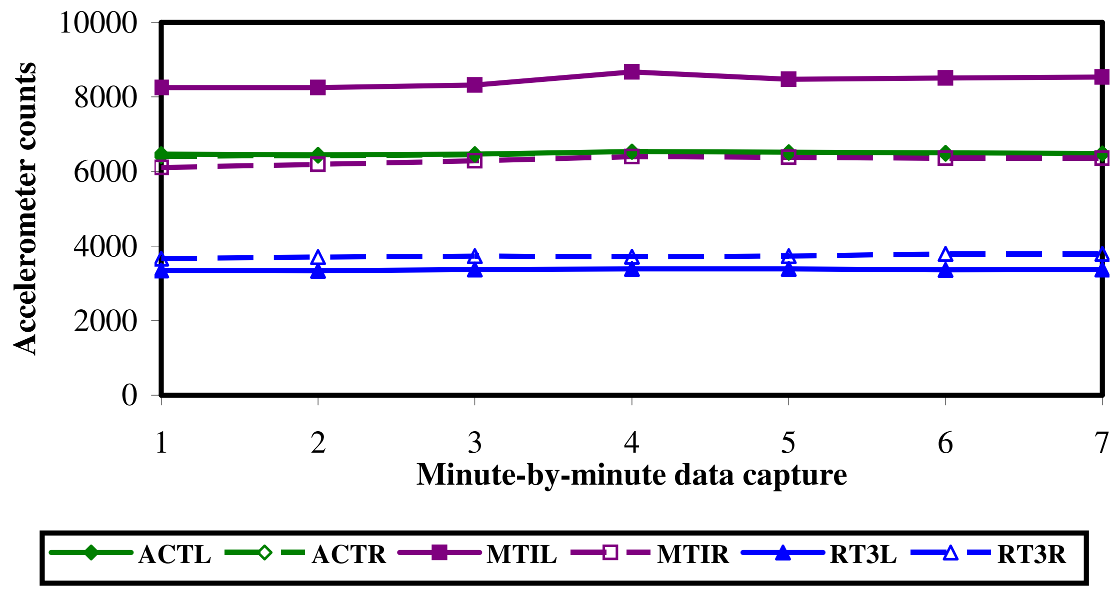


Figure 3.3 Comparison of minute-by-minute accelerometer counts between left and right devices of Actical, MTI, and RT3 monitors.

The results indicate that there is a linear increase in accelerometer counts across speed categories for Actical, MTI, and RT3 models. The plots also illustrate that for both left and right devices, accelerometer counts are highest in the MTI, then Actical, and lowest in the RT3. This finding is of no surprise, since each model has its own specific range of accelerometer counts and therefore counts among the models are not directly comparable. Post-hoc tests illustrated that mean counts were not significantly different between left and right Actical devices ($p>0.05$), across speeds 1, 2, and 3. In the MTI and RT3, mean counts were not significantly different between left and right devices at speed 1 and 2 ($p>0.05$), however were significantly different at speed 3 ($p<0.01$). Profile plots of the estimated marginal means illustrate that again, accelerometer counts are highest in the MTI, then Actical, and lowest in the RT3 models, however accelerometer counts remain stable in all models from minute 1 to minute 7, with the exception of the MTI. This indicates that there is little variation in mean accelerometer counts recorded from minute to minute at each separate speed for all models.

The results of the repeated measures ANOVA provided verification for the illustrated findings on accelerometer counts assessed with both left and right devices of each model utilized in this research study.

3.7 INTRA-DEVICE RELIABILITY IN ACCELEROMETERS

Intra-device reliability assesses the consistency of measurement within a device when a repeated stimulus is applied. In this design, intra-device reliability was assessed by examining the variation in accelerometer counts from minute 1 to minute 7 for each device at each speed. Coefficients of variation (CV-intra) for each device were obtained and compared across speed. The coefficient of variation is a statistic that provides a relative measure of data dispersion compared to the mean. Previous research suggests that a low CV indicates good reliability (Atkinson and Nevill, 1998), as the amount of variation in data collected is small. Tables 3.5 and 3.6 demonstrate the relationship between intra-device reliability and speed, and Figure 3.4 illustrates a summary comparison.

Table 3.5 Comparison of intra-device variation in accelerometer counts in left AMP, Actical, MTI and RT3 activity monitors across speed.

SPEED (KM/H)	LEFT MODEL	N	% OF DATA CAPTURE	MEAN COUNTS	SD	SEM	CV
4	AMP	12	29.2	115	3.8	3.8	3.3
	Actical	41	100.0	1989	125.0	19.5	6.3
	MTI	35	85.3	2045	218.2	36.9	10.7
	RT3	41	100.0	1471	152.6	23.8	10.4
5	AMP	16	32.7	112	4.0	0.9	2.8
	Actical	49	100.0	2879	111.9	16.0	3.9
	MTI	45	91.8	3636	280.7	41.9	7.7
	RT3	49	100.0	1897	144.5	20.6	7.6
6	AMP	9	31.0	122	2.2	0.7	1.8
	Actical	29	100.0	4143	140.7	26.1	3.4
	MTI	27	93.1	5236	397.5	76.5	7.6
	RT3	29	100.0	2373	147.5	27.4	6.2
7	AMP	9	37.5	131	6.0	2.0	4.6
	Actical	24	100.0	7559	318.0	65.0	4.2
	MTI	21	87.5	12022	1463.0	319.2	12.2
	RT3	24	100.0	3977	275.8	56.3	6.9
8	AMP	16	45.7	134	8.1	2.0	6.1
	Actical	30	85.7	10334	256.4	46.8	2.5
	MTI	28	80.0	14821	1075.9	203.3	7.3
	RT3	34	97.1	4917	337.9	58.0	6.9
9	AMP	12	41.4	141	6.4	1.9	4.6
	Actical	27	93.1	11054	280.1	53.9	2.5
	MTI	25	86.2	14863	1351.9	270.4	9.1
	RT3	29	100.0	5081	321.6	59.7	6.3
10	AMP	9	33.3	129	8.4	2.8	6.5
	Actical	21	77.8	11582	237.8	51.9	2.1
	MTI	25	92.6	15889	1491.3	298.3	9.4
	RT3	27	100.0	5470	373.5	71.9	6.8
11	AMP	4	44.4	150	3.1	1.6	2.1
	Actical	6	66.7	11436	254.9	104.1	2.2
	MTI	6	66.7	13152	937.1	382.6	7.1
	RT3	9	100.0	5915	338.1	112.7	5.7
12	AMP	5	33.3	129	8.1	3.6	6.3
	Actical	7	46.7	11702	175.9	66.5	1.5
	MTI	14	93.3	16732	916.0	244.8	5.5
	RT3	15	100.0	6035	425.9	110.0	7.1

Table 3.6 Comparison of intra-device variation in accelerometer counts in right AMP, Actical, MTI and RT3 activity monitors across speed.

SPEED (KM/H)	RIGHT MODEL	N	% OF DATA CAPTURE	MEAN COUNTS	SD	SEM	CV
4	AMP	23	56.1	112	2.5	0.5	2.2
	Actical	41	100.0	1796	117.4	18.3	6.5
	MTI	39	95.1	1957	190.9	30.6	9.8
	RT3	40	97.6	1609	173.4	27.4	10.8
5	AMP	32	65.3	114	3.8	0.7	3.3
	Actical	49	100.0	2658	103.7	14.8	3.9
	MTI	48	98.0	3358	255.1	36.8	7.6
	RT3	49	100.0	2069	186.3	26.6	9.0
6	AMP	22	75.9	122	2.3	0.5	1.9
	Actical	29	100.0	4034	147.2	27.3	3.7
	MTI	27	93.1	5182	471.0	90.6	9.1
	RT3	29	100.0	2628	159.4	29.6	6.1
7	AMP	15	62.5	131	5.9	1.5	4.6
	Actical	24	100.0	7809	319.2	65.2	4.1
	MTI	22	91.7	7855	695.1	148.2	8.9
	RT3	24	100.0	4536	346.8	70.8	7.7
8	AMP	24	68.6	150	3.4	0.7	2.2
	Actical	26	74.3	10428	292.2	57.3	2.8
	MTI	33	94.3	9283	436.2	75.9	4.7
	RT3	34	97.1	5398	388.2	66.6	7.2
9	AMP	25	86.2	147	4.5	0.9	3.1
	Actical	24	82.8	10882	246.5	50.3	2.3
	MTI	27	93.1	9965	817.0	157.2	8.2
	RT3	29	100.0	5470	362.1	67.3	6.6
10	AMP	21	77.8	148	3.7	0.8	2.5
	Actical	19	70.4	11786	217.1	49.8	1.8
	MTI	25	92.6	11607	418.2	83.6	3.6
	RT3	27	100.0	5746	388.3	74.7	6.8
11	AMP	9	100.0	150	4.0	1.3	2.7
	Actical	9	100.0	11229	202.1	67.4	1.8
	MTI	8	88.9	13080	607.0	214.6	4.6
	RT3	9	100.0	5889	327.3	109.1	5.6
12	AMP	14	93.3	147	4.2	1.1	2.9
	Actical	5	33.3	11436	342.8	153.3	3.0
	MTI	14	93.3	13660	684.9	183.1	5.0
	RT3	15	100.0	6149	381.5	98.5	6.2

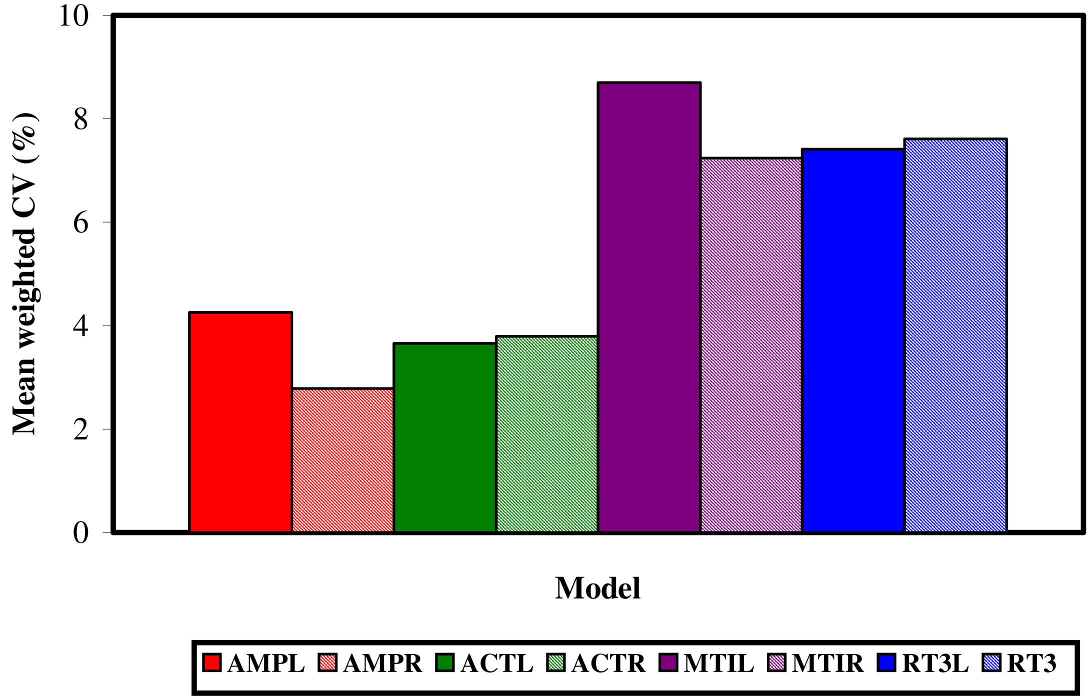


Figure 3.4 Comparison of overall intra-device variation in accelerometer counts in left and right AMP, Actical, MTI, and RT3 activity monitors.

The results reveal very different trends in intra-device variation between the four models used across speed. In order to assess whether intra-device variation in accelerometer counts was significantly different at certain speeds, an analysis of variance with a Bonferroni correction for multiple comparisons ($p<0.05$) was utilized. In the left AMP, although not significantly different ($p>0.05$), within-instrument variation (CV-intra) appeared to be lowest at 6 km/h and highest at 10 km/h. In the MTI device, although not significantly different ($p>0.05$), intra-device variation appeared to be highest at 7 km/h and lowest at 12 km/h. The left Actical and left RT3 devices showed similar trends. Intra-device variation was significantly highest in the Actical at 4 km/h ($p<0.05$; significantly different from all speeds except 7 and 11 km/h) and at 4 km/h for the RT3 ($p<0.05$). Intra-device variation was significantly lowest in the Actical at 12 km/h ($p<0.05$; only significantly different from 4 km/h) and significantly lowest in the RT3 at 11 km/h ($p<0.05$; only significantly different from 4 km/h). In the right devices, intra-device variation was significantly highest at the slowest speed (i.e., 4 km/h) for Actical ($p<0.05$; significantly different from all speeds except 7 and 12 km/h) and RT3 devices ($p<0.05$; significantly different from all speeds except 5 km/h) and significantly lowest at faster speeds (i.e., 10 km/h and 11 km/h respectively; $p<0.05$; only significantly different from 4 km/h). Although not significantly different ($p>0.05$), intra-device variation in the MTI appeared to be highest at the slowest speed (i.e., 4 km/h) and lowest at a fast speed (i.e., 11 km/h). Intra-device variation in the AMP was significantly lowest at 6 km/h ($p<0.05$; only significantly different from 7 km/h) and highest at 7 km/h ($p<0.05$; only significantly different from 4, 5, 6, and 8 km/h). Overall, these results suggest that the variation within devices is high at very slow speeds for Actical and RT3 monitors and low at very fast speeds. The reverse appears to be occurring for the AMP model.

Overall mean weighted coefficients of variation (CV-intra) were calculated for all models (see Figure 3.4). These analyses took into account the number of cases (i.e., N) of available data at each speed and multiplied that number by the CV at that speed. Overall mean weighted coefficients were then calculated to represent within-device variation for each accelerometer model across all speeds combined. These results reveal that within-device variation in left monitors was lowest in the Actical (CV% = 3.7), and increased from the AMP (CV = 4.3%) to the RT3 (CV = 7.4%) to the MTI (CV = 8.7%). In the right devices, intra-device variation was lowest in the AMP (CV% = 2.8) and increased from the Actical (CV = 3.8%) to the MTI (CV = 7.2%) to the RT3

(CV = 7.8%). Trends for overall mean CV's between left and right devices were different for all models.

The percentage of good data available for intra-device reliability analyses was very different for each model used. For both left and right devices, the AMP had the lowest percentage of good data available (mean = 56.4%), considerably lower than all other models used. The Actical had the next lowest percentage of good data available (mean = 85.1%), followed by the MTI (mean = 89.8%) and the RT3 (99.6%). A greater amount of good data was available from left Actical and RT3 devices compared to right devices and right AMP and MTI devices compared to left devices across all speeds.

3.8 INTER-DEVICE RELIABILITY IN ACCELEROMETERS

Inter-device reliability describes the variation in scores between two or more instruments. In this study, it was assessed by having each participant wear two devices of the same activity monitor model simultaneously at approximately the same location on the body (i.e. hip placement – left versus right). The inter-device reliability was then assessed by calculating mean differences in accelerometer counts between left and right devices, converting these into a coefficient of variation (CV inter) and plotting these values against speed. As a result, it was possible to visualize how inter-device reliability varied across speed while making comparisons to other models. Results are presented in Table 3.7.

Table 3.7 Comparison of inter-device variation in accelerometer counts in AMP, Actical, MTI and RT3 activity monitors across speed.

SPEED (KM/H)	MODEL	N	% OF DATA CAPTURE	MEAN COUNTS	SD	SEM	CV	ICC
4	AMP	10	24.4	116	3.1	1.0	2.7	1.0
	Actical	41	100.0	1893	121.2	18.9	6.4	0.7
	MTI	33	80.5	2008	210.7	36.7	10.5	0.8
	RT3	40	97.6	1539	163.6	25.9	10.6	0.8
5	AMP	11	22.5	123	2.6	0.8	2.1	1.0
	Actical	49	100.0	2768	107.8	15.4	3.9	0.8
	MTI	44	89.8	3452	266.9	40.2	7.7	0.6
	RT3	49	100.0	1983	165.4	23.6	8.3	0.8
6	AMP	7	24.1	123	2.8	1.1	2.3	0.9
	Actical	29	100.0	4088	143.9	26.7	3.5	1.0
	MTI	25	86.2	5170	435.2	87.0	8.4	0.6
	RT3	29	100.0	2500	153.5	28.5	6.1	0.9
7	AMP	7	29.2	137	6.7	2.5	4.9	1.0
	Actical	24	100.0	7684	318.6	65.0	4.2	1.0
	MTI	19	79.2	9883	1065.5	244.5	10.8	0.3
	RT3	24	100.0	4256	311.3	63.6	7.3	0.8
8	AMP	13	37.1	142	5.2	1.4	3.6	0.6
	Actical	26	74.3	10293	279.0	54.7	2.7	0.9
	MTI	27	77.1	11962	754.0	145.1	6.3	0.2
	RT3	34	97.1	5157	363.1	62.3	7.0	0.6
9	AMP	11	37.9	146	5.1	1.6	3.5	0.5
	Actical	23	79.3	10888	256.5	53.5	2.4	0.9
	MTI	24	82.8	11893	936.7	191.2	7.9	0.5
	RT3	29	100.0	5276	341.8	63.5	6.5	0.5
10	AMP	8	29.6	135	5.9	2.1	4.4	0.4
	Actical	19	70.4	11657	231.6	53.1	2.0	0.7
	MTI	23	85.2	13879	884.7	184.5	6.4	0.4
	RT3	27	100.0	5608	380.9	73.3	6.8	0.6
11	AMP	4	44.4	150	3.3	1.7	2.2	0.4
	Actical	6	66.7	11332	228.5	93.3	2.0	0.8
	MTI	5	55.6	13018	877.0	392.2	6.7	0.6
	RT3	9	100.0	5902	332.7	110.9	5.6	0.6
12	AMP	5	33.3	138	6.1	2.7	4.4	0.1
	Actical	5	33.3	11530	253.4	113.3	2.2	1.1
	MTI	14	93.3	15196	800.5	213.9	5.3	0.3
	RT3	15	100.0	6092	403.7	104.2	6.6	0.7

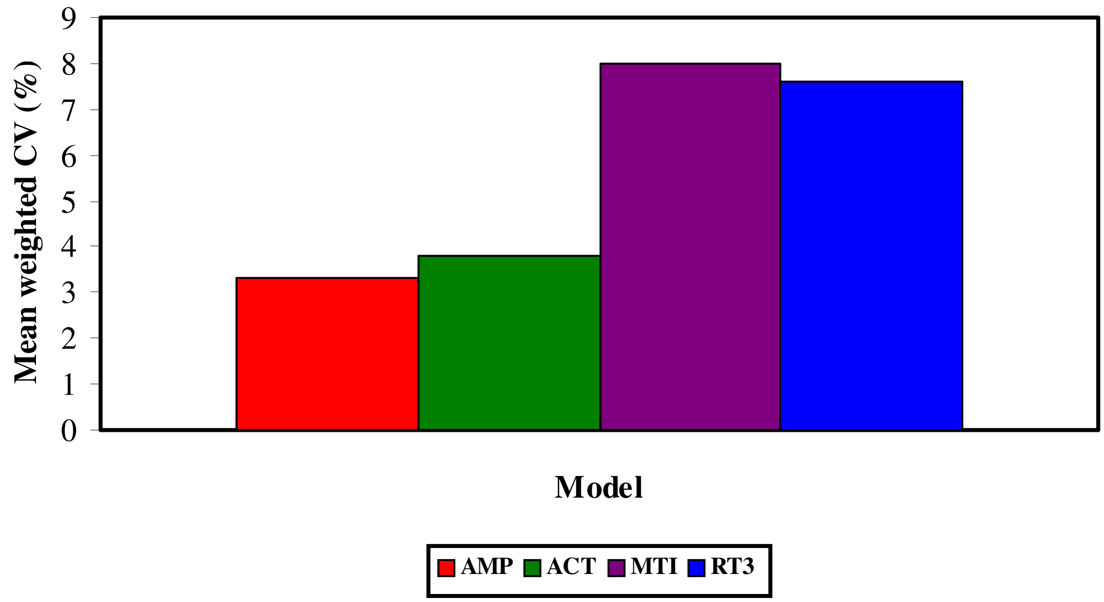


Figure 3.5 Comparison of overall inter-device variation in accelerometer counts in AMP, Actical, MTI, and RT3 activity monitors.

Analyses of inter-device variation in accelerometer counts reveal similar trends to those found in intra-device reliability analyses specific to each model. Inter-device variation was significantly highest at slower speeds (i.e., 4 km/h) for Actical ($p<0.05$; significantly different from all speeds except 7 and 12 km/h) and RT3 devices (i.e., $p<0.05$; significantly different from all speeds except 5 km/h) and lowest at very high speeds (i.e., 10 km/h; $p<0.05$; only significantly different from 4 km/h). Although there were no statistically significant differences in inter-device variation across speed in the MTI ($p>0.05$), inter-device variation appeared to be lowest at a mid-range speed (i.e., 7 km/h) and highest at a fast speed (i.e., 11 km/h). In the AMP model, although variation in counts between left and right devices was not significantly different across speed ($p>0.05$), inter-device variation appeared to be lowest at a slow speed (i.e., 5 km/h) and highest at a mid-range speed (i.e., 7 km/h). Overall mean inter-device variation across all speeds (see Figure 3.5) was lowest in the AMP (CV = 3.3%), increasing from the Actical (CV = 3.8%) to the RT3 (CV = 7.6%) to the MTI (CV = 8.0%).

When comparing overall mean inter-device variation across speeds between models, it is important to assess the percentage of good data used in the assessment of this statistic. For example, even though the AMP and Actical models had equal CV%'s, only 31.4% of total data collected was used with the AMP, while 80.4 % was used with the Actical. The MTI had an even greater percent of overall good data available for analyses (i.e., 81.1%), however the most amount of good data available came from the RT3 model (i.e., 99.4%).

3.9 INTER-MODEL RELIABILITY IN ACCELEROMETERS

In this study, inter-model reliability was assessed by examining the variation in output between different models of motion sensors. Data presented in Tables 3.3, 3.4 and 3.5 enables comparisons of coefficients of variation (CV-intra and CV-inter) amongst devices and across all speeds (i.e., 4 to 12 km/h) to be made.

3.10 INTRA AND INTER-DEVICE RELIABILITY IN YAMAX PEDOMETERS

The Yamax pedometers used in this study provided total step counts over each seven minute testing interval for speeds 1, 2 and 3. Since it was not possible to collect minute-by-minute data, an analysis of intra-device reliability could not be performed in the same manner as conducted in the accelerometer models. Nevertheless, it was possible to investigate the variation in step counts within a certain speed (i.e., coefficient of variation within-speed). Additionally, the variation in steps counted between left and right Yamax models at each speed (i.e., inter-device variation across speed) was also calculated. This information is presented in Tables 3.8 and 3.9.

Table 3.8 Variation in step counts collected through visual counting (VC) and Yamax pedometers across all treadmill speeds.

SPEED (KM/H)	MODEL	N	% OF DATA CAPTURE	MEAN STEPS	SD	SEM	CV
4	VC steps	41	100.0	109.9	8.7	1.4	7.9
	L Yamax	41	100.0	104.8	19.2	3.0	18.3
	R Yamax	41	100.0	102.1	17.5	2.7	17.1
N=41							
5	VC steps	49	100.0	118.6	10.1	1.4	8.5
	L Yamax	49	100.0	118.3	9.3	1.3	7.8
	R Yamax	49	100.0	119.4	10.0	1.4	8.3
N=49							
6	VC steps	29	100.0	126.3	12.5	2.3	9.9
	L Yamax	29	100.0	127.3	12.3	2.3	9.6
	R Yamax	29	100.0	127.6	11.8	2.2	9.2
N=29							
7	VC steps	24	100.0	155.7	23.0	4.7	14.7
	L Yamax	24	100.0	156.1	22.9	4.7	14.7
	R Yamax	24	100.0	156.1	23.2	4.7	14.9
N=24							
8	VC steps	34	100.0	167.3	13.5	2.3	8.1
	L Yamax	34	100.0	168.2	13.8	2.4	8.2
	R Yamax	34	100.0	168.1	13.8	2.4	8.2
N=34							
9	VC steps	29	100.0	160.3	15.6	2.9	9.8
	L Yamax	29	100.0	162.3	10.7	2.0	6.6
	R Yamax	29	100.0	162.1	10.9	2.0	6.7
N=29							
10	VC steps	27	100.0	159.4	9.1	1.8	5.7
	L Yamax	27	100.0	158.8	8.7	1.7	5.5
	R Yamax	27	100.0	158.8	8.6	1.7	5.4
N=27							
11	VC steps	9	100.0	161.6	11.2	3.7	6.9
	L Yamax	9	100.0	160.7	9.6	3.2	6.0
	R Yamax	9	100.0	160.7	9.7	3.2	6.0
N=9							
12	VC steps	15	100.0	160.6	7.9	2.1	5.0
	L Yamax	15	100.0	160.8	8.0	2.1	5.0
N=15	R Yamax	15	100.0	161.0	7.9	2.0	4.9

Table 3.9 Comparison of inter-device variation in Yamax pedometer steps across speed.

SPEED (KM/H)	MODEL	N	% OF DATA CAPTURE	DIFFERENCE STEPS	SD	SEM	CV
4	Yamax	41	100.0	2.7	1.8	0.3	1.2
5	Yamax	49	100.0	1.1	0.7	0.1	0.5
6	Yamax	29	100.0	0.3	0.5	0.1	0.4
7	Yamax	24	100.0	0.0	0.3	0.1	0.2
8	Yamax	34	100.0	0.0	0.1	0.0	0.0
9	Yamax	29	100.0	0.2	0.2	0.0	0.1
10	Yamax	27	100.0	0.0	0.0	0.0	0.0
11	Yamax	9	100.0	0.0	0.1	0.0	0.1
12	Yamax	15	100.0	0.1	0.1	0.0	0.0

A visual count of steps taken during the three treadmill conditions was performed for each participant and used as the criterion standard in which to compare steps recorded with the Yamax pedometers. Steps were visually counted for 5 out of the 10 minutes for each treadmill bout. The results indicate this method produced the overall lowest variation (CV = 8.5%) in steps across all speeds compared to the left Yamax (CV = 9.1%) and right Yamax (CV = 9.0%). The greatest variation in steps recorded by the Yamax occurred at 4 km/h and was lowest at higher speeds (i.e., 10 km/h, 11 km/h, and 12 km/h). This can be attributed to the fact that a greater percentage of total participants in this study walked at this speed compared to the other speeds in the first treadmill condition (i.e., 5 km/h and 6 km/h). Consequently, there would be greater variation in mean leg length, stride length and therefore stride frequency at this speed. The highest speeds in this study were performed by a lower percentage of total participants, who tended to be older and taller. As a result, there would be considerably less variation in leg length, stride length and therefore stride frequency at these speeds. It should be noted that the Yamax pedometers provided 100% good data in this study, an obvious strength that is critical for physical activity monitoring. Table 3.6 shows excellent agreement between VC counts and Yamax counts at all but the lowest speed (4 km/h).

3.11 VALIDITY OF ACTIVITY MONITORS

3.11.1 Relationship between accelerometer counts and measured energy expenditure

Previous research has shown a direct relationship between accelerometer counts and energy expenditure, where an increase in counts is associated with an increase in energy expenditure. Accelerometer counts (i.e., mean of minute 1 to 7 for each separate speed category) from the AMP, Actical, MTI and RT3 were plotted against measured energy expenditure to observe this relationship. Data from right devices only is portrayed, as the most complete data was available from right-mounted devices. The results are illustrated in Figures 3.6, 3.7, 3.8, and 3.9.

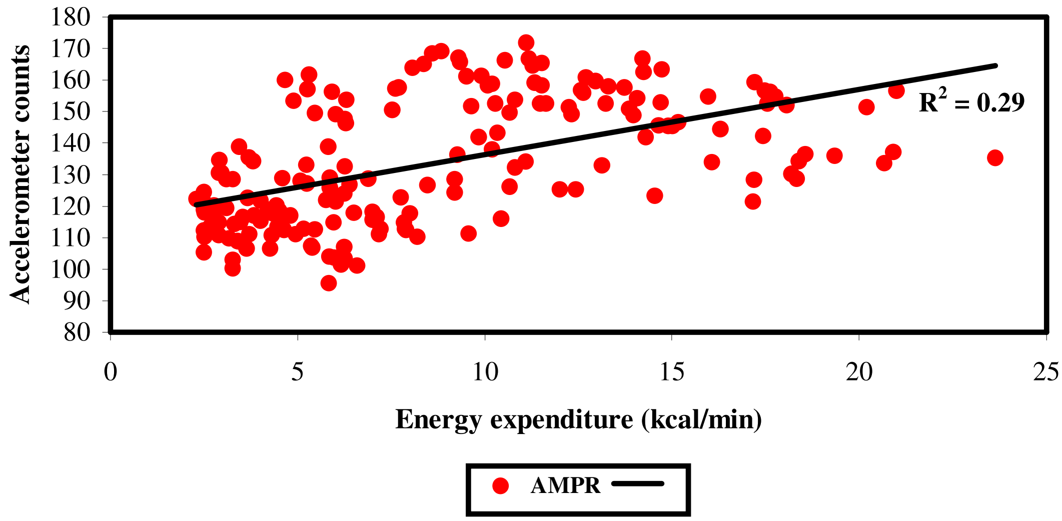


Figure 3.6 Relationship between AMP accelerometer counts and energy expenditure.

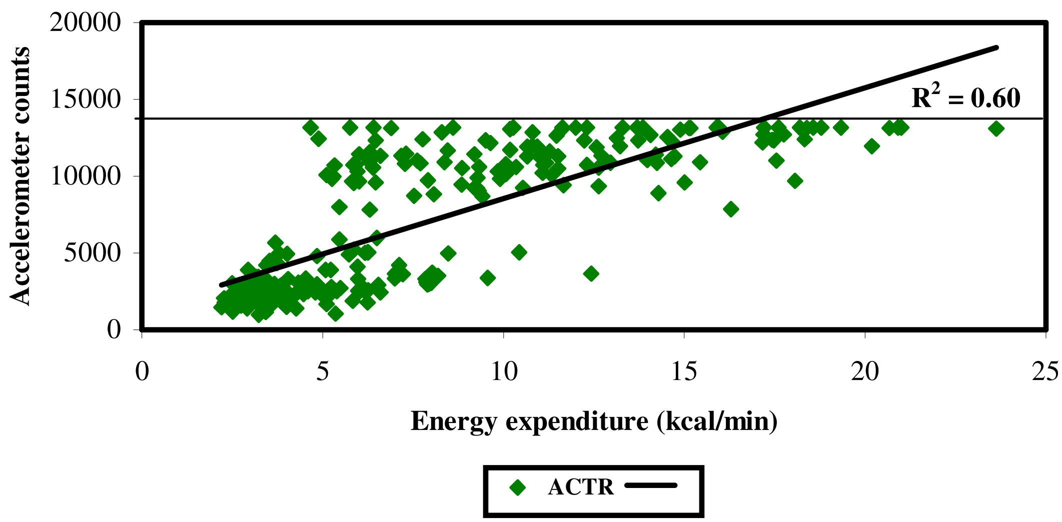


Figure 3.7 Relationship between Actical accelerometer counts and energy expenditure.[4]

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[4] Note: Horizontal line on graph (i.e., at approximately 13176 counts) represents level of saturation in the Actical device. Due to the effects of frequency-dependent filtering, counts will appear to cluster just under this level of saturation. As a result, it is difficult to interpret the R^2 value.

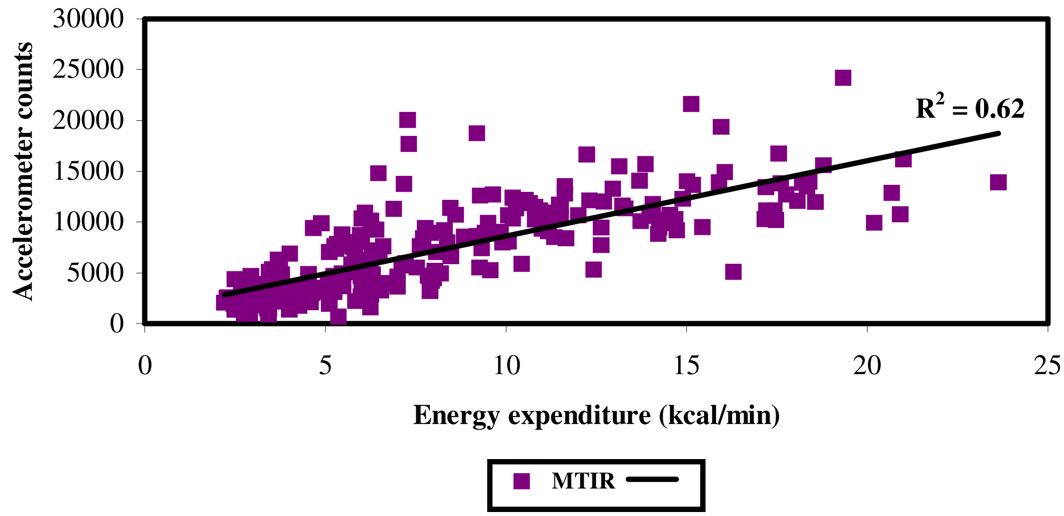


Figure 3.8 Relationship between MTI accelerometer counts and energy expenditure.

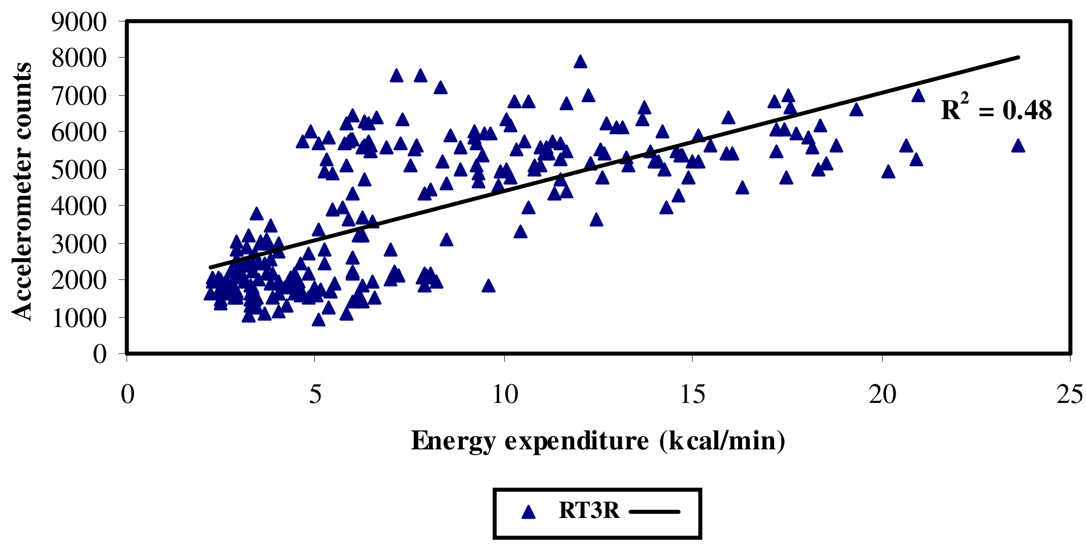


Figure 3.9 Relationship between RT3 accelerometer counts and energy expenditure.

The relationship between accelerometer counts and energy expenditure was similar for each model utilized in this study. In the AMP, Actical and MTI models, it appears that accelerometer counts increase linearly with energy expenditure up until a point, after which they begin to plateau or become more variable despite increases in energy expenditure. This plateau is most evident in the Actical model. In the AMP and MTI models, it appears that at a certain level, accelerometer counts become more variable. In the RT3 model however, there appears to be a consistent linear relationship between accelerometer counts and energy expenditure, where counts continue to rise with increases in energy expenditure. These trends suggest that energy expenditure predictions based on accelerometer counts may be inaccurate at high speeds and therefore stride frequencies for certain activity monitors.

3.11.2 Correlations between predicted energy expenditure and measured energy expenditure

Another primary objective of this research project was to determine the ability of four models of accelerometers (i.e., AMP, Actical, MTI and RT3) and one pedometer model (i.e., Yamax) to predict energy expenditure. Previous research suggests that accelerometer devices can quantify energy expenditure, assuming that movement (or acceleration) of the limbs and torso is closely related with whole body energy expenditure (Bassett, 2000; Freedson and Miller, 2000; Haskell et al., 1993). Accelerometers detect changes in activity energy expenditure by converting count scores into energy expenditure though an appropriate equation. Similarly, pedometers use step counts and distance traveled within an equation to generate an estimate of calories expended during activity.

In this study, validation of the AMP, Actical, MTI, RT3 and Yamax models was accomplished through correlations of activity energy expenditure (kcal/min) measured through respiratory gas analysis (the criterion standard measure) to activity energy expenditure estimated by these models. The alpha level was set at $p = 0.05$. Correlation coefficients for all speeds are presented in Table 3.10.

Table 3.10 Correlations between energy expenditure predicted using accelerometer counts (or steps) and energy expenditure measured through respiratory gas analysis

SPEED CATEGORY	LEFT MODEL	N	% OF DATA CAPTURE	R^2	RIGHT MODEL	N	% OF DATA CAPTURE	R^2	MEAN (L&R)
1	AMP	22	25.6	0.86	AMP	56	65.1	0.67	0.77
	Actical	86	100.0	0.86	Actical	86	100.0	0.88	0.87
	MTI	77	89.5	0.83	MTI	82	95.3	0.69	0.76
	RT3	86	100.0	0.83	RT3	85	98.8	0.83	0.83
	Yamax	86	100.0	0.92	Yamax	86	100.0	0.92	0.92
N=86									
2	AMP	38	44.2	0.48	AMP	62	72.1	0.33	0.41
	Actical	78	90.7	0.92	Actical	76	88.4	0.94	0.93
	MTI	78	90.7	0.67	MTI	82	95.3	0.87	0.77
	RT3	86	100.0	0.94	RT3	86	100.0	0.92	0.93
	Yamax	86	100.0	0.96	Yamax	86	100.0	0.96	0.96
N=86									
3	AMP	32	37.6	0.26	AMP	67	77.9	0.33	0.30
	Actical	70	82.4	0.88	Actical	61	70.9	0.92	0.90
	MTI	71	83.5	0.38	MTI	79	91.9	0.79	0.59
	RT3	85	100.0	0.90	RT3	85	98.8	0.87	0.89
	Yamax	85	100.0	0.96	Yamax	85	98.8	0.96	0.96
N=85									

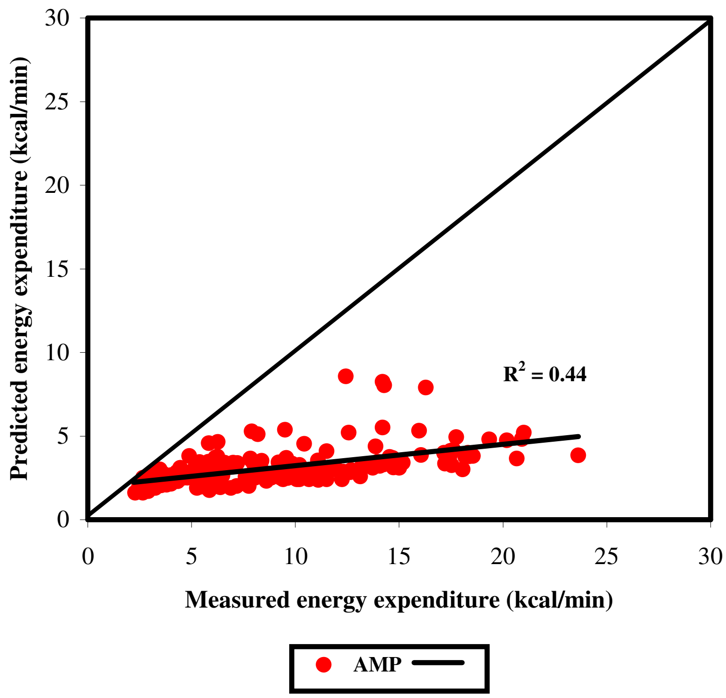
Correlations between predicted energy expenditure and measured energy expenditure were quite high (see Table 3.10) for Actical, RT3, and Yamax monitors for speeds 1 to 3 (R^2 = 0.83 to 0.96), however were low to moderate for the AMP and MTI (R^2 = 0.26 to 0.87). When calculating the average of both left and right monitors, the results illustrate that the Yamax pedometer provided the best estimation of energy expenditure for all three speeds (speed 1, R^2 = 0.92; speed 2, R^2 = 0.96; speed 3, R^2 = 0.96). However, correlation coefficients were also very high for the Actical (R^2 = 0.87,

$R^2 = 0.93$, $R^2 = 0.90$), RT3 ($R^2 = 0.83$, $R^2 = 0.93$, $R^2 = 0.89$) and MTI ($R^2 = 0.76$, $R^2 = 0.77$, $R^2 = 0.59$) models for speeds 1, 2 and 3 respectively. The AMP activity monitor provided its best estimation of energy expenditure at speed 1 ($R^2 = 0.77$), however its predictive utility was noticeably lower for speeds 2 and 3 ($R^2 = 0.41$, $R^2 = 0.30$). The effect of speed on energy expenditure predictions varied with each model. Although not statistically different from the other speeds, the Actical, MTI, RT3 and Yamax models appeared to provide the best estimation at speed 2, which ranged from 5 to 10 km/hr.

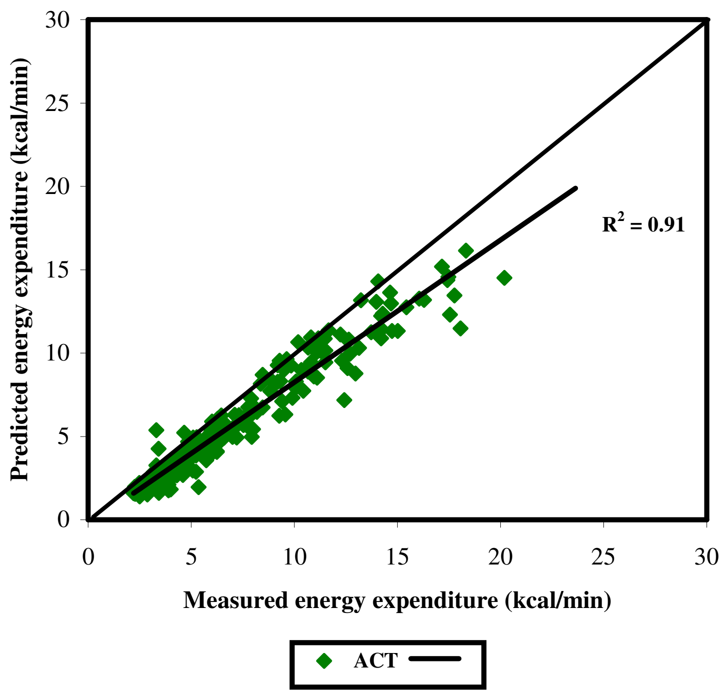
When reviewing these correlations, it is important to consider the number of observations (i.e., N) that contributed to the statistic. Incomplete data and outliers occurred more frequently with certain models. Saturation of data occurred in both Actical and MTI devices, while incomplete data in the AMP monitors resulted in the elimination of many observations. Only in the RT3 (with the exception of 2 cases) and the Yamax were data complete for all participants. If all data collected were included in these analyses, then correlations between predicted energy expenditure and measured energy expenditure would likely be significantly lower for the AMP, Actical and MTI.

3.11.3 Relationship between predicted energy expenditure and measured energy expenditure

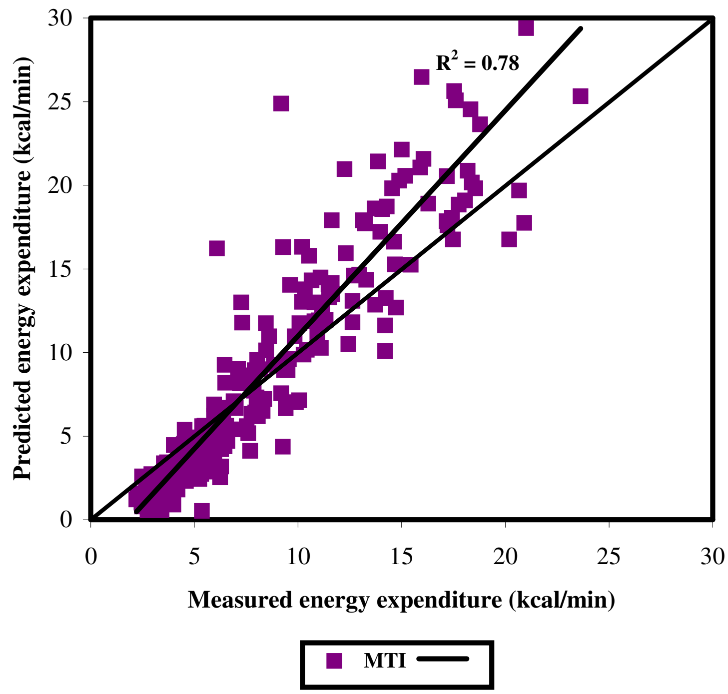
Although correlations revealed that there were strong relationships between predicted energy expenditure and measured energy expenditure from all activity monitors (with the exception of the AMP) across speeds 1 to 3, these correlations could not identify any patterns that might exist. As a result, energy expenditure measured through expired gas analysis was plotted against predicted energy expenditure for each separate model. The results for all right devices are displayed in Figure 3.10.



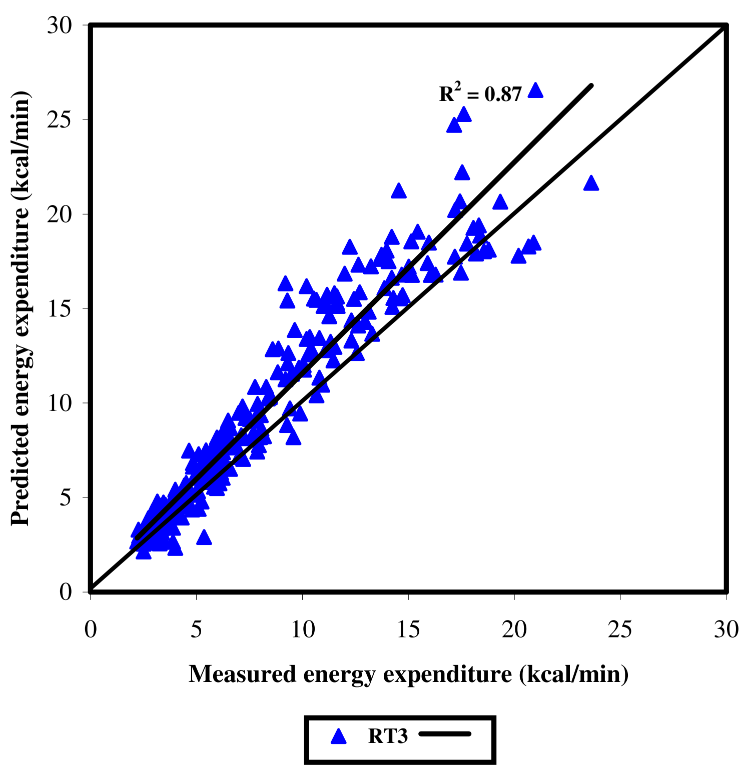
Predicted energy expenditure (kcal/min)
Measured energy expenditure (kcal/min)
$R^2 = 0.44$
AMP



Predicted energy expenditure (kcal/min)
Measured energy expenditure (kcal/min)
$R^2 = 0.91$
ACT



R^2 = 0.78
Predicted energy expenditure (kcal/min)
Measured energy expenditure (kcal/min)
0
5
10
15
20
25
30
MTI



R^2 = 0.87
Predicted energy expenditure (kcal/min)
Measured energy expenditure (kcal/min)
0
5
10
15
20
25
30
RT3

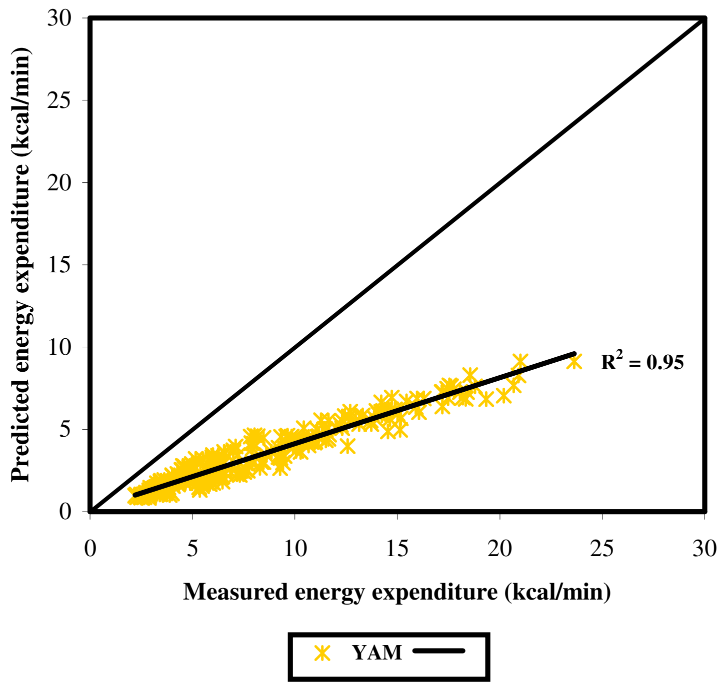


Figure 3.10 Relationship between predicted energy expenditure and measured energy expenditure for AMP, Actical, MTI, RT3 and Yamax activity monitors.

These results indicate that the relationship between predicted and measured energy expenditure is unique to each model. The AMP appears to consistently underestimate energy expenditure; beyond measured energy expenditure of approximately 10 kcal/min, these predictions become more variable. In the Actical, there appears to be strong correlations between predicted and measured energy expenditure up until approximately 15 kcal/min, after which predicted energy expenditure starts to plateau. In the MTI, there seems to be strong correlations between predicted and measured energy expenditure until approximately 10 kcal/min, after which the MTI appears to overestimate energy expenditure. Although there are fairly strong correlations between predicted and measured energy expenditure in the RT3, this model appears to consistently overestimate energy expenditure. Finally, despite a very strong linear relationship between predicted and measured energy expenditure, the Yamax appears to consistently underestimate energy expenditure.

3.11.4 Mean differences in energy expenditure (kcal/min) between predicted energy expenditure and measured energy expenditure across speeds 1, 2 and 3

Mean differences between energy expenditure predicted from the AMP, Actical, MTI, RT3 and Yamax models and energy expenditure measured through respiratory gas analysis were calculated and analyzed using one sample t-tests in order to determine whether models tended to underestimate or overestimate energy expenditure at certain treadmill speeds. Results for the right devices of all models are illustrated in Figure 3.11.

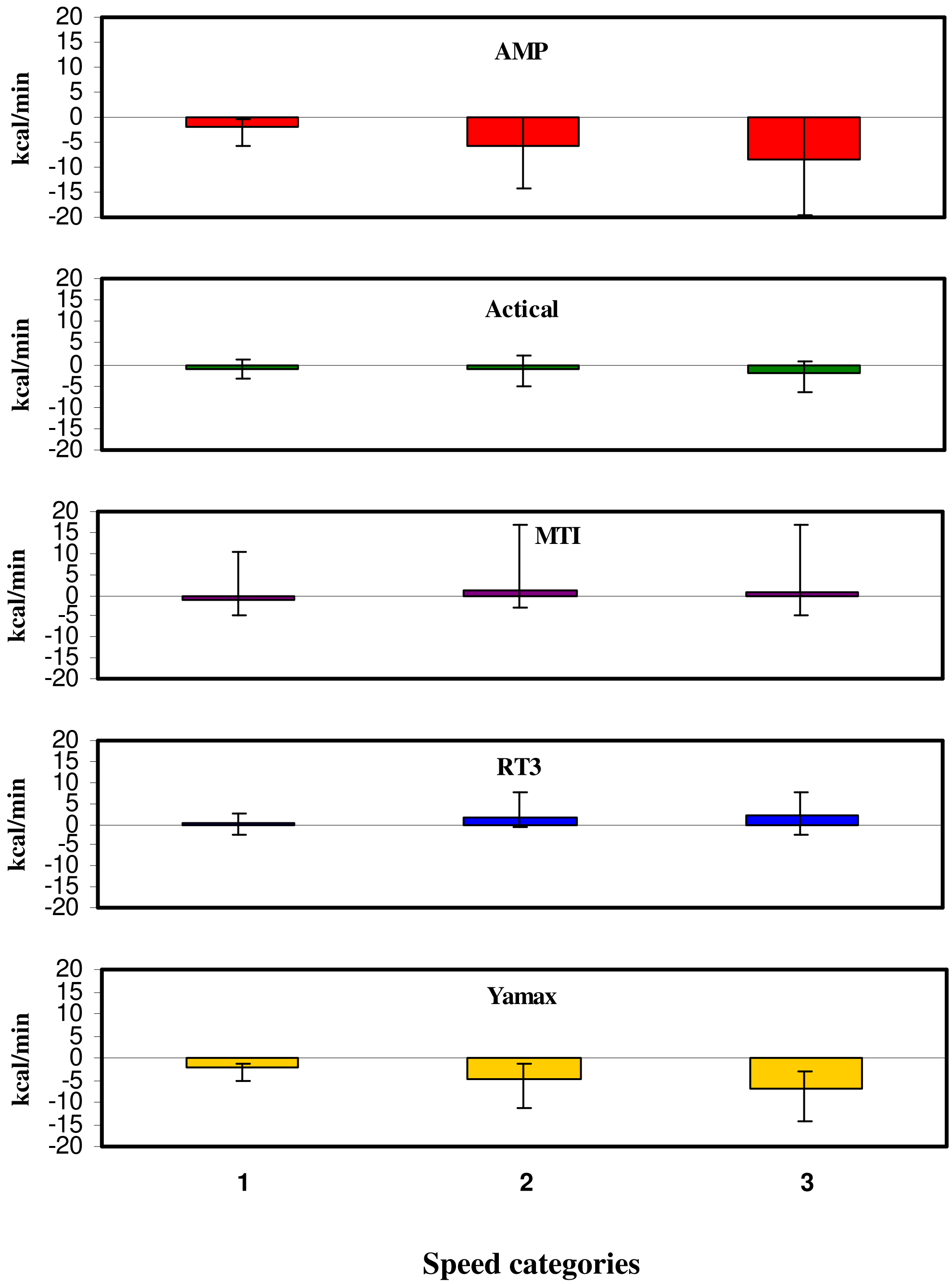


Figure 3.11 Mean (i.e., across seven minutes) differences between predicted energy expenditure and energy expenditure measured by respiratory gas analysis from the right AMP, right Actical, right MTI, right RT3 and right Yamax for speeds 1-3.[5]

[5] Note: Error bars represent the range in mean differences for each device at speed categories 1, 2, and 3.

The AMP, Actical and Yamax models appear to consistently underestimate energy expenditure at speeds 1 (walk), 2 (walk/jog) and 3 (run). The MTI appears to typically underestimate energy expenditure during treadmill walking at speed 1, and then over-predict energy expenditure to a greater extent as participants transitioned into a faster walk/jog and finally a run. The RT3 appears to consistently overestimate energy expenditure at all conditions. T-test analyses revealed that mean differences between predicted and measured energy expenditure were significantly different from zero for AMP, Actical, MTI, and RT3 devices for speeds 1, 2, and 3 ($p<0.01$); the only exception being the MTI at speed 3 ($p>0.05$). As a result, all underestimations/overestimations reported by these devices were significant. Mean differences in energy expenditure from the criterion standard were calculated for speeds 1, 2, and 3 and then combined to give an overall score. These results revealed that the AMP, Actical and Yamax models underestimated participants' energy expenditure [mean difference (right devices) = -5.7 kcal/min, -1.3 kcal/min, and -4.7 kcal/min respectively; $p<0.01$] and therefore may not have appropriately rewarded individuals for energy expended during the treadmill activity bouts. The MTI and RT3 devices appeared to over-predict energy expenditure during these conditions (mean difference = 0.3 kcal/min and 1.4 kcal/min, respectively; $p<0.01$) and thus suggest that participants may have been working harder than they really were.

3.11.5 Mean differences in energy expenditure (kcal/min) between predicted energy expenditure and measured energy expenditure within height categories and across speeds 1, 2, and 3

It was hypothesized that differences in height and leg length among individuals might directly affect the ability of activity monitors to provide a valid estimation of energy expenditure across a variety of speeds. Height quintiles were created to investigate mean differences between predicted energy expenditure (i.e., from AMP, Actical, MTI, RT3, and Yamax models) at speeds 1, 2, and 3 and measured energy expenditure (i.e., from respiratory gas analysis). Height quintiles were labeled 1 to 5 and represent standing heights of 133.7 cm (range = 125.5 to 138.7 cm), 145.3 cm (range = 139.0 to 155.3 cm), 162.1 cm (range = 156.0 to 166.2 cm), 173.0 cm (166.8 to 179.6 cm), and 186.2 cm (range = 181.0 to 196.1 cm), respectively. Comparisons of mean differences between models and within height categories for the three speed categories were performed to determine which models provided the most accurate estimates of energy expenditure for individuals of different heights and whether the accuracy changed for different speeds. Results are displayed in Figures 3.12, 3.13, and 3.14

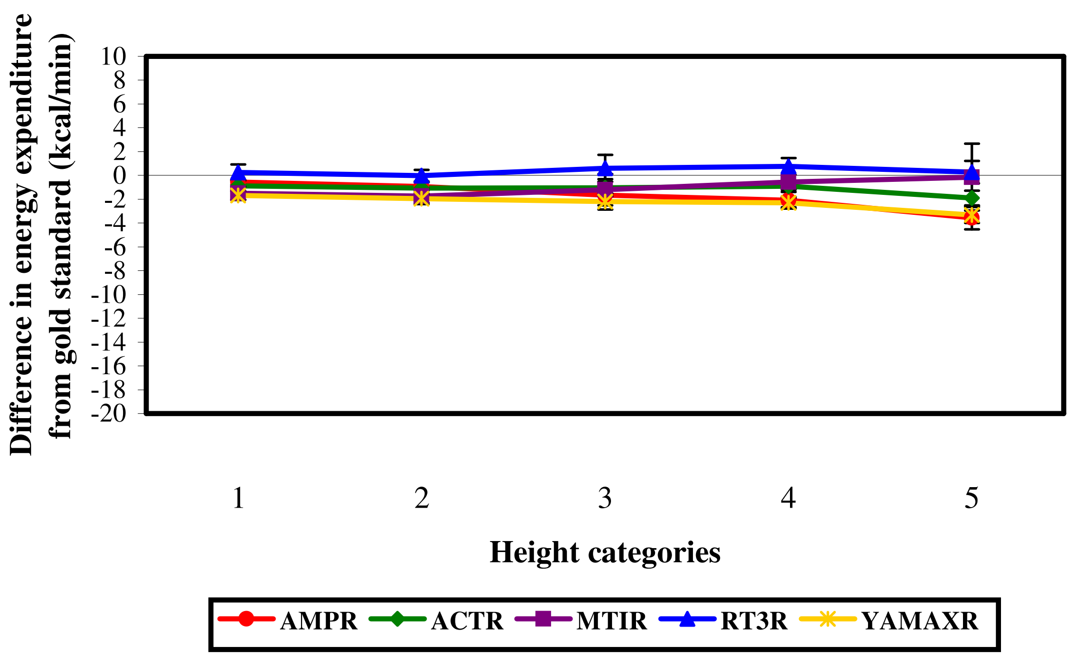


Figure 3.12 Mean differences between predicted and measured energy expenditure across five height quintiles for speed 1.

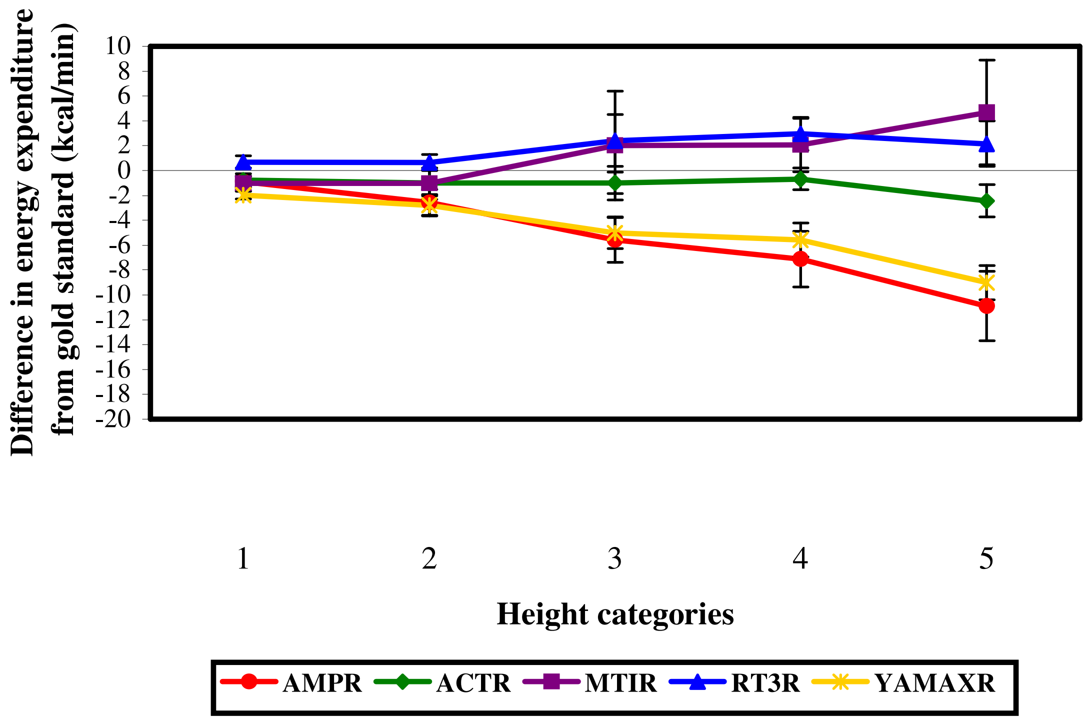


Figure 3.13 Mean differences between predicted and measured energy expenditure across five height quintiles for speed 2.

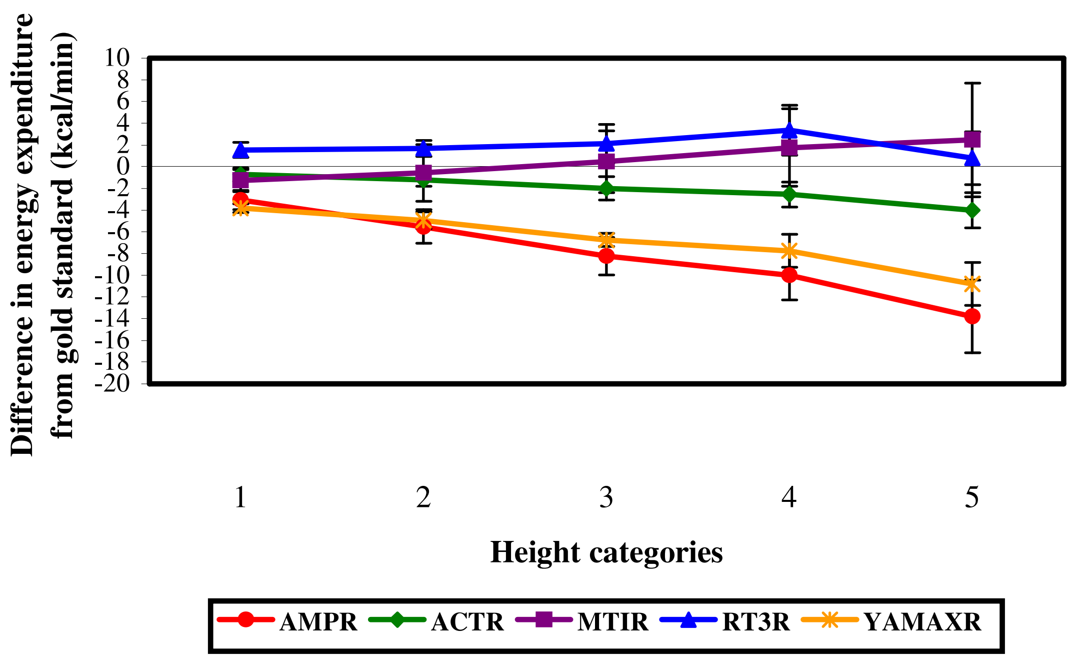


Figure 3.14 Mean differences between predicted and measured energy expenditure across five height quintiles for speed 3.

Simple effects/interactions were explored using simple effects analysis and a Bonferroni correction for multiple comparisons ($p<0.05$). Data was analyzed in order to assess whether there were significant mean differences between predicted and measured energy expenditure across the two extreme height categories (i.e., 1 and 5). Post hoc tests confirmed that mean differences between predicted and measured energy expenditure were significantly greater for the tallest individuals in comparison to the shortest individuals ($p<0.05$) across all speeds.

The results displayed in Figures 3.12 to 3.14 reveal very different trends for energy expenditure prediction accuracy across height categories and across speed, which are unique to each model. At speed 1 (4 to 6 km/h), all height categories considered, the AMP provided significantly greater underestimations of energy expenditure than the Actical and MTI ($p<0.05$), while the Yamax provided significantly greater underestimations than the Actical and the MTI ($p<0.05$). There were no statistically significant differences in energy expenditure prediction between either the AMP and the Yamax ($p>0.05$) or the Actical and the MTI ($p>0.05$). The RT3 provided significantly greater overestimations of energy expenditure than all other models ($p<0.05$). At speed 2 (5 to 10 km/h), all height categories considered, the AMP and Yamax provided significantly greater underestimations of energy expenditure than the Actical and the MTI ($p<0.05$); there were no statistically significant differences between the AMP and the Yamax ($p<0.05$). The RT3 provided significantly greater overestimations of energy expenditure than all models ($p<0.05$) except for the MTI ($p>0.05$), which began to over-predict energy expenditure for taller individuals (i.e., height categories 3 to 5). At speed 3 (7 to 12 km/h), when all height categories were considered, the AMP provided significantly greater underestimations of energy expenditure than the Actical, MTI, and Yamax ($p<0.05$), while the RT3 provided significantly greater overestimations of energy expenditure than all models, except for the MTI ($p>0.05$), which again started to overestimate energy expenditure for taller participants (i.e., height categories 3 to 5).

When comparing energy expenditure predictions across speeds, results revealed that the Actical, AMP, and Yamax provided the greatest underestimations of energy expenditure at speed 3 when compared to speeds 2 and 1 ($p<0.05$). The MTI and RT3 both overestimated energy expenditure to the greatest extent at speed 3 ($p<0.05$).

3.11.6 Characteristics of saturation data

Saturation data was labeled as an outlier and therefore eliminated for all analyses in this research design. Despite this, an investigation was performed in order to examine certain characteristics, such as age, leg length, stride length and stride frequency associated with this data. Furthermore, mean differences between energy expenditure predicted using saturated data and energy expenditure measured through respiratory gas analysis were calculated in order to determine whether saturated data overestimated or underestimated energy expenditure within these cases. The results are presented in Table 3.11.

Table 3.11 Descriptive characteristics of participants with saturation data.[6]

	CASES	SPEED (KM/H)	AGE	LL (CM)	SL (CM)	SF	COUNTS	ACTL	ACTR	MTIL	MTIR
		4	18	79.9	0.7	97.7				32767	
N	**2**									**2**	
		5	8	74.6	0.6	132.5				32767	
N	**1**									**1**	
		6	28	85.2	0.7	142.3				32767	
N	**1**									**1**	
		7	8	74.6	0.7	180.5				32767	
N	**1**									**1**	
		8	15	75.8	0.8	162.6		13096	12689	32767	
N	**14**							**4**	**8**	**2**	
		9	17	77.3	0.9	155.8		12930	12928	32767	13763
N	**9**							**2**	**5**	**1**	**1**
		10	22	83.7	1.1	155.5		13064	13118	25020	
N	**15**							**6**	**8**	**1**	
		11	24	86.1	1.2	158.9		13156	13166		
N	**6**							**3**	**3**		
		12	23	87.2	1.3	159.9		13136	13146	32365	10671
N	**20**							**8**	**10**	**1**	**1**
T	**69**							**23**	**34**	**10**	**2**

[6] Note: This table represents all saturated data reported from Actical and MTI activity monitors. Descriptive characteristics of participants (i.e., age, leg length, stride length and stride frequency) are shown to indicate that accelerometer counts began to level-off at slower speeds for younger, shorter participants (with very high stride frequencies) and faster speeds for older, taller participants (with very high stride frequencies). Accelerometer counts represent the mean of 7 minutes of data for each case, and are expressed as the grand mean (mean counts/total # of cases) for each speed. Saturated data (i.e., MTI counts of 32767 or Actical counts of 13176) are embedded within this data.
Abbreviations: LL = leg length; SL = stride length; SF = stride frequency; N = number of cases of saturated data; T = total cases of saturated data.

Saturated data occurred only in the Actical and MTI models and was more frequent in the Actical than in the MTI. These results illustrate that fewer cases of saturation occurred at lower speeds than higher speeds, which is not surprising considering that saturation of data occurs at high levels of body acceleration. However, when saturation did occur at lower speeds (i.e., 5 km/h and 7 km/h), the participants were very young, had short leg lengths and stride lengths in comparison to other cases. At 7 km/h, saturation occurred in an eight–year old, whose stride frequency at that speed was much higher than those cases in which saturation occurred at higher speeds for older and taller individuals (i.e., 10 km/h, 11 km/h, and 12 km/h). At the higher speeds, saturation occurred in older individuals with longer leg lengths and stride lengths, however stride frequency was fairly low in comparison to stride frequencies represented in other cases of saturation.

Predicted energy expenditure (kcal/min) from saturated data was also analyzed and compared to energy expenditure measured through expired gas analysis in order to determine whether it provided an underestimation or overestimation of energy expenditure. Findings were very different for Actical and MTI models. The Actical model underestimated energy expenditure (overall total difference in energy expenditure = -19.1 kcal/minute for both left and right devices), while the MTI overestimated energy expenditure (overall total difference in energy expenditure = 215.5 kcal/min for both left and right devices) for all cases of saturation. Based on these results, it is quite clear that the MTI overestimated energy expenditure to a far greater extent than the Actical underestimated energy expenditure in the majority of cases of saturated data.

3.11.7 Energy expenditure equations utilized by activity monitors

Energy expenditure equations were different for all five models used. These equations were developed by the manufacturer/company of each model using various predictor variables (i.e., age, height, weight). The equations are presented in Table 3.12.

Table 3.12 Manufacturer-designed energy expenditure equations for AMP, Actical, MTI, RT3 and Yamax models.[7]

	ENERGY EXPENDITURE EQUATIONS
AMP	EE = RMR (kcal/sec) * MET value * time interval (sec)
Actical	EE (children) = 0.03534 + [1.135E-5 * counts] * weight (kg)
	EE (adults) = 0.2663 + [1.107E-5 * counts] * weight (kg)
MTI	EE = 0.0000191 * counts * weight (kg)
RT3	EE (males) = $\frac{[473 * \text{weight (lb)}] + [(971 * \text{height (in)}] – [(513 * \text{age}] + 4687}{100{,}000}$
	EE (females) = $\frac{[331 * \text{weight (lb)}] + [(352 * \text{height (in)}] – [353 * \text{age}] + 49854}{100{,}000}$
Yamax	EE = distance (miles/minute) * weight (lbs) * 0.35

These equations suggest that the predictor variables selected and the relative weight of these predictor variables to help estimate activity energy expenditure differ amongst models. As a result, it appears that the selection of additional predictor variables to help explain the variance in accelerometer counts (or alternatively steps) and estimate energy expenditure may differ between models.

[7] Note: Actical energy expenditure equations classify individuals age 8 to 17 as children and individuals age 18+ as adults.

3.12 DEVELOPMENT OF ENERGY EXPENDITURE EQUATIONS

Another objective of this research study was to develop energy expenditure equations for each specific model, using accelerometer counts (or step counts with the Yamax pedometer) and certain predictor variables (i.e., age, weight, leg length). Correlations between counts/steps and participant characteristics (i.e., age, standing height, leg length, weight, BMI, waist circumference, sum of five skinfolds, speed, distance, stride length and stride frequency) were calculated and examined in order to find out the relationships among each variable. Covariance between these variables was also assessed. Selected variables were then entered one variable at a time into multiple regression analyses. This enabled an investigation of the improvement in the regression model with the addition or elimination of certain variables. Four variables were selected to help explain the variance in energy expenditure: accelerometer counts, weight, leg length and age. Energy expenditure, our dependent variable, was expressed as an absolute measure [i.e., kcal/min, calculated from VO_2 (L/min)]. Table 3.13 displays energy expenditure equations for each model at speeds 1, 2, and 3.

Table 3.13 Energy expenditure prediction equations developed from data collected in this research study at speeds 1, 2, and 3.[8]

		REGRESSION EQUATION (KCAL/MIN)	R^2	SEE
1	AMP	y = -7.210 + 0.06997 [weight (kg)] + 0.06487 [leg length (cm)] - 0.0435 (age) + 0.03227 [counts (min)]	0.87	0.69
	Actical	y = -3.579 + 0.05963 [weight (kg)]+ 0.05756 [leg length (cm)] -0.0592 (age) + 0.000573 [counts(min)]	0.90	0.57
	MTI	y = -2.252 + 0.06262 [weight (kg)]+ 0. 04512 [leg length (cm)] -0.214 (age) + 0.000211[counts (min)]	0.87	0.66
	RT3	y = -4.346 + 0.06548 [weight (kg)] + 0.05758 [leg length (cm)]–0.0485 (age) + 0.000906[counts (min)]	0.88	0.62
	Yamax	y = -4.000 + 0.06614 [weight (kg)] + 0.05705 [leg length (cm)] - 0.0520 (age) + 0.01220 [steps (min)]	0.85	0.69
2	AMP	y = -17.246 + 0.126 [weight (kg)] + 0.175 [leg length (cm)] + 0.03865 [counts (min)]	0.91	1.43
	Actical	y = -6.656 + 0.120 [weight (kg)] + 0.07427 [leg length (cm)] + 0.005032 [counts (min)] - 0.0710 (age)	0.95	0.98
	MTI	y = -9.444 + 0.09959 [weight (kg)] + 0. 123 [leg length (cm)] + 0.003599 [counts (min)]	0.92	1.31
	RT3	y = -11.379 + 0.108 [weight (kg)] + 0.120 [leg length (cm)] + 0.001117 [counts (min)]	0.93	1.26
	Yamax	y = -19.642 + 0.113 [weight (kg)] + 0.167 [leg length (cm)] + 0.06171 [steps (min)]	0.90	1.49
3	AMP	y = -10.627 + 0.139 [weight (kg)] + 0.08244 [leg length (cm)] + 0.004955 [distance (m/min)]	0.94	1.22
	Actical	y = -9.688 + 0.148 [weight (kg)] + 0.09540 [leg length (cm)] + 0.0004637 [counts (min)]	0.92	1.15
	MTI	y = -9.594 + 0.146 [weight (kg)] + 0.142 [leg length (cm)] + 0.0001784 [counts (min)]	0.92	1.48
	RT3	y = -13.223 + 0.153 [weight (kg)] + 0.161 [leg length (cm)] + 0.0006314 [counts (min)]	0.91	1.49
	Yamax	y = -10.627 + 0.139 [weight (kg)] + 0.08244 [leg length (cm)] + 0.004955 [distance (m/min)]	0.94	1.22

The regression equations for AMP, Actical, MTI, RT3 and Yamax activity monitors were developed using variables that were significant predictors of energy expenditure ($p<0.05$). These equations were developed using accelerometer counts and Yamax pedometer steps recorded from right devices only. A combination of data from left and right devices was not used due to inter-device variation among activity

[8] Note: In this table, bolded numbers 1, 2, and 3 refer to speed categories 1 (4 to 6 km/h), 2 (5 to 10 km/h), and 3 (7 to 12 km/h). Variables have been entered into all equations according to order of predictive ability. SEE refers to the standard error of the estimate.

monitors. A greater percentage of complete data was available from right devices, and therefore only this data was included.

The coefficients for each variable in all equations were ordered according to their unique correlation (i.e., R^2 value) with energy expenditure. For all equations, weight appeared to be the most significant independent predictor of energy expenditure. Accelerometer counts were significant predictors of energy expenditure for all models at all speeds, with the exception of the AMP at speed category 3. Yamax pedometer steps were significant predictors of energy expenditure for speed category 1 and 2, but not speed category 3. Leg length was a significant predictor of energy expenditure in all speed categories for the AMP, Actical, MTI, RT3 and Yamax models. Age was a significant predictor of energy expenditure only in speed category 1 (for all models) and in speed category 2 for the Actical.

The predictive power of all regression equations increased from speed 1 to speed 2 to speed 3. The only exception to this was the RT3, in which the regression equation for speed 2 provided the best estimation of energy expenditure. If all regression equations are considered, it seems that a combination of accelerometer counts (or steps in the Yamax's case), age, leg length and weight help to explain anywhere from 85 to 94 percent of the variance in energy expenditure.

CHAPTER FOUR: DISCUSSION

The primary objective of this research project was to assess the influence of leg length, stride length and stride frequency on accelerometer counts and energy expenditure using four accelerometer models (AMP, Actical, MTI and RT3) and one pedometer model (Yamax). The reliability of these models was assessed by calculating intra-device, inter-device and inter-model variation in accelerometer counts across three treadmill conditions. The concurrent validity of these models was determined by comparing predicted energy expenditure (i.e., calculated using accelerometer counts in model-specific equations) to the criterion standard (i.e., energy expenditure assessed through respiratory gas analysis). Accelerometer counts and Yamax pedometer steps, in combination with age, weight and leg length, were then be entered into regression equations in order to determine whether the addition of these variables could explain more of the variance in energy expenditure. These analyses were performed to identify whether individual differences in stride length and stride frequency influence a device's reliability and validity in assessing energy expenditure. Collectively, these results contribute to our understanding of the significant factors necessary to obtain a valid measure of an individual's energy expenditure when performing physical activity.

4.1 HYPOTHESIS ONE

It was hypothesized that accelerometer counts recorded across the three treadmill conditions in this study would reach a plateau at lower speeds for participants with shorter leg lengths and stride lengths (and therefore greater stride frequencies), than participants with longer legs. An accelerometer is designed to measure accelerations of the body or body segment to which it is fixed. The dynamic range, or the ability to capture physical activity, is unique to each accelerometer model; accelerations outside of the typical range of human movement are filtered. Previous research has illustrated that at high speeds (i.e., running), the frequency and intensity of body accelerations may exceed the passband of the accelerometer, causing accelerometer counts to reach a plateau (Brage et al., 2003c). Based on these findings, it was further believed that differences in leg length, stride length and stride frequency among participants would cause variations in count scores and energy expenditure both within devices, between devices, and between models across all speeds tested. As a result, it was expected that the accelerometers would not be rewarding participants for energy expended at higher speeds (or intensity) of activity.

In this research study, participants were able to select three treadmill speeds from a range provided (i.e., 4 to 12 km/h). Descriptive data presented in Tables 3.2, 3.3 and 3.4 indicates that in general, the slowest speeds in each speed category were chosen by the youngest, lightest and shortest participants, while the oldest, heaviest and tallest participants chose the highest speeds. Physical fitness however was a large contributing factor. Those who were very young and/or physically unfit tended to choose slower speeds so that they could successfully complete the test. In speed category 1, stride length was longest for the fastest speed (i.e., 6 km/h), however stride frequency was only significantly different between 4 km/hr and 6 km/h. In speed category 2 and 3, it appeared that when looking at both extremes (i.e., 5 km/h and 10 km/h; 7 km/hr and 12 km/h, respectively), those participants at the lowest speeds were significantly younger, had shorter leg lengths and stride lengths. Although stride frequency was much higher for participants walking/jogging at 10 km/h than 5 km/h (i.e., in speed category 2), when participants transitioned into a run, it appeared that those participants running at 7 km/h had significantly higher stride frequencies than those running at 12 km/h.

A relationship between stride frequency and accelerometer counts was also identified. In the AMP, Actical, and MTI models, the data revealed a linear increase in accelerometer counts with increasing stride frequency up to a point, after which accelerometer counts began to level off or become more variable with any further increases in stride frequency. In the RT3 model, a strong linear relationship was maintained across stride frequency. Previous research has suggested that in uniaxial accelerometers (i.e., those that measure vertical accelerations), counts may begin to level off at high stride frequencies and as a result, predicted energy expenditure might be underestimated (Brage et al., 2003c). Accelerometer counts were plotted against energy expenditure measured through expired gas analysis to determine whether increases in energy expenditure were associated with an increase in accelerometer counts, or whether accelerometer counts began to plateau despite rises in energy expenditure. Results revealed that in the AMP, Actical, and MTI models, counts began to either plateau or become more varied with increases in energy expenditure. In the RT3 however, increases in accelerometer counts mirrored increases in energy expenditure. In order to determine whether or not this phenomenon was associated with an underestimation of energy expenditure, mean differences between predicted energy expenditure and energy expenditure measured through expired gas analysis were calculated. These results illustrated the AMP, Actical, and Yamax models provided the greatest underestimation of energy expenditure during speed 3, the running condition, in which the highest stride frequencies occurred.

Since previous research has suggested that variables such as leg length and stride length may affect accelerometer counts and energy expenditure prediction (Brage et al., 2003c), participants were sorted into five height categories (i.e., 1 to 5, mean heights = 133.7 cm, 145.3 cm, 162.1 cm, 173.0 cm, and 186.2 cm, respectively) to investigate which models provided the most valid estimates of energy expenditure for individuals of different heights and whether validity varied across speed (see Figures 3.12 to 3.14). At speed 3, the greatest underestimation and overestimation of energy expenditure occurred for all participants ($p<0.05$). The AMP, Actical and Yamax models provided the greatest underestimation of energy expenditure for the tallest individuals (i.e., height category 5; $p<0.05$). The RT3 provided the greatest overestimation of energy expenditure for the tallest participants. At speed 3, the MTI tended to underestimate energy expenditure for shorter individuals (i.e., height categories 1 and 2) and overestimate energy expenditure for taller individuals (i.e., height categories 3, 4, and 5).

When considering the results of these analyses in combination with one another, it becomes possible to address the first hypothesis. These results revealed that in the running bout (speed category 3), the lowest speed (i.e., 7 km/h) was chosen by the youngest participants, who had the shortest legs and stride lengths when compared to those who chose the fastest speed (i.e., 12 km/h). Participants who ran at 7 km/h had significantly greater stride frequencies than those who ran at 12 km/h. Previous research indicates that at a given speed, younger individuals will have higher stride frequencies than older participants, which is due to shorter leg lengths and stride lengths (Schepens et al., 1998). These data show that accelerometer counts may level off at high stride frequencies and that this leveling-off may result in the underestimation of energy expenditure from certain models (i.e., AMP, Actical, and Yamax). As a result, it appears that energy expenditure may be underestimated at lower speeds for participants who are younger, have shorter leg lengths and lower stride lengths compared to participants who are older, have longer legs and higher stride lengths running at faster speeds. This supports the theory that leg length and stride frequency directly affect accelerometer counts and the estimation of energy expenditure.

4.1.1 Saturation of accelerometer counts

Previous research has identified that in accelerometers designed to assess vertical acceleration, counts may become saturated (i.e., hit a ceiling) at high stride frequencies (Brage et al., 2003c). Based on this theory, it was expected that saturation of counts would occur most frequently during the running treadmill bout (i.e., speed 3) in this study. Correlations between stride length and stride frequency across the three treadmill conditions were calculated in order to assess this relationship and its affects on the appearance of saturated data. Pearson product moment correlations revealed significant relationships between stride length and stride frequency. For speed 3, there was a significant negative association between stride length and stride frequency, and a positive relationship between stride length and stride frequency for speed 2. There was no significant relationship between stride length and stride frequency at speed 1. These results suggest that when running, there is a trade-off between stride length and stride frequency, where increases in stride length are associated with decreases in stride frequency, or alternatively, decreases in stride length are associated with increases in stride frequency. When participants transitioned from a typical walk into a faster walk or jog however, an increase in stride length was related to an increase in stride frequency. As a result, it was expected that saturation of accelerometer counts would most likely occur for those who maintained a very high stride frequency.

A total of 69 cases of saturated data were identified, occurring only in the Actical and MTI. Both of these models are most sensitive to accelerations in the vertical plane of motion, which supports the previous theory. The results in Table 3.11 reveal that for younger participants, accelerometer counts from the Actical and the MTI began to level-off between 7 to 8 km/h, while for older participants, counts began to level-off at higher speeds. The data further indicates a direct relationship between leg length, stride length, stride frequency and saturated data. Younger participants chose to run at lower speeds than older individuals, as shorter leg lengths and stride lengths would have made it physically challenging to maintain faster speeds. Older, taller participants were able to tolerate faster speeds because of greater leg lengths and stride lengths. In order to maintain the last speed however, an increase in stride frequency had to occur. The results illustrate that increases in stride frequency with speed are related to a leveling off of accelerometer counts, and that this leveling off does occur at slower speeds for younger, shorter individuals and faster speeds for older, taller individuals.

The unique design properties of each accelerometer model utilized in this research study can explain why saturated data occurred in some models and not others. In the MTI accelerometer, when a change in body acceleration is detected, a sensor within the device generates a charge that is proportional to the magnitude of the acceleration. The signal is then filtered by highpass and lowpass filters; the lower and upper cutoff frequencies are 0.21 and 2.28 Hz, respectively (Tryon and Williams, 1996). Outside of these frequencies, signals are reduced in amplitude. The Actical model is capable of detecting frequencies from 0.5 to 3.0 Hz and converting these into numeric counts. The RT3 accelerometer has a dynamic range of 0.05 to 2.00 G and is sensitive to frequencies in the range of 0.5 to 10 Hz (Powell et al., 2003).

In this research project, step frequency (steps/min) was measured at speeds 1, 2, and 3. As a result, the dynamic ranges of each accelerometer model [expressed in Hz (cycles per second)] were converted into step frequency. In these terms, calculations indicate the dynamic range of the MTI to be 12.6 to 136.8 steps/minute. The Actical model has a calculated range of 30 to 180 steps/min. Based on these calculations, both the RT3 and AMP models are able to detect step frequencies well beyond the highest values recorded in this study (i.e., RT3 = 3 to 600 steps/min; AMP = 0 to 24,000 steps/min).

The results of this study indicate that saturation occurred in the MTI model below its upper range (i.e., 136.8 steps/min) on three occasions (stride frequencies = 98.3, 97, and 132.5). All cases of saturation occurred below the upper range of the Actical (i.e., 180 steps/min). However, due to complex biomechanical patterns of movement during walking and running, it is very difficult to equate the dynamic range of an accelerometer, expressed in steps/min, to the stride frequency of a human participant. As a result, it is difficult to state that these accelerometers should have been capable of detecting certain stride frequencies and not have reported saturated data.

Careful examination of saturated data was necessary to determine whether saturation occurred as a result of the upper range of the device being exceeded or rather a malfunction of the device. In the MTI, it appeared that all of the saturated data occurred due to device malfunctions. This conclusion was based on the following reasons. For two participants, saturated data was present at speed 1, 2, and 3, which suggests that the device must not have been working properly. In other cases, accelerometer counts were not saturated consistently across the seven minutes of recorded data, which also suggests the device malfunctioned. In the Actical, it appeared that 51% of saturated data occurred due to malfunctions, while 49% of saturated data occurred due to accelerations that exceeded the upper limit of the device.

The ability of saturated data to predict energy expenditure varied between Actical and MTI models and also across speed. It was hypothesized that as accelerometer counts began to level off for individuals, this would result in an underestimation of energy expenditure. The results indicate that saturated data in the MTI accelerometer provided extreme overestimations of energy expenditure for participants (see Table 3.11). This may be explained by the equation that the MTI model uses to calculate energy expenditure. This equation uses a combination of accelerometer counts and weight (kg), with a correction factor, to calculate energy expenditure (see Table 3.12). Since saturation in the MTI was identified at 32767 counts, when included into the equation, this would provide an overestimation of energy expenditure; the overestimation would likely be even higher if the participant's weight was higher. For example, saturated data (i.e., 32767 counts/min) occurred at speed 8 in a ten year old who weighed 27.5 kg. Energy expenditure assessed through expired gas analysis was 5.3 kcal/min. Based on the MTI equation, this would translate into an overestimation of 11.9 kcal/min in energy expenditure. Saturation data in the Actical consistently underestimated energy expenditure. The Actical also uses a combination of accelerometer counts and weight (kg), with a correction factor, in its equation to calculate energy expenditure (see Table 3.12).

One limitation of this research design was that the last speed was physically challenging for some participants. As a result of this, some participants opted for lower speeds in order to complete the test. If the duration of the testing protocol had been lower (i.e. 5 minutes instead of 10), participants may have chosen slightly higher speeds in which to run. As a result, the stride frequencies of a greater percentage of participants may have been higher for speed 3. Since accelerometer counts were shown to level off at higher stride frequencies, this may have resulted in the appearance of more saturated data. Nevertheless, high intensity running speeds are relatively rare among an average population.

The results of this research project, when examined in combination with one another, support the first hypothesis, which stated that a leveling-off of count scores would occur at lower speeds for individuals with shorter leg lengths and stride lengths (and therefore greater stride frequencies) than individuals with longer legs.

4.2 HYPOTHESIS TWO

According to the second hypothesis, the magnitude of intra-device, inter-device and inter-model variation would differ between the AMP, Actical, MTI and RT3 activity monitors.

4.2.1 Intra-device reliability

Intra-device variation in accelerometer counts was generally highest at very slow speeds and lowest at very fast speeds for both left and right Actical and RT3 activity monitors. Previous research has indicated that intra-device reliability decreases at extreme values of acceleration, and that step frequency may be an important factor (Brage et al., 2003a). At speeds lower than 11 km/h, the average acceleration during the contact phase of the running stride is equal to the average acceleration of the aerial phase, which is 1 G (Cavagna et al., 1988). At speeds above 11 km/h though, the average contact phase acceleration increases with shorter contact duration. Since many accelerometers are only able to measure accelerations and frequencies within a certain range, specific to each model, it could be that at very high running speeds, these ranges are exceeded and therefore counts will start to level off. The fact that the lowest intra-device variation in accelerometer counts was seen at the highest speeds in Actical and RT3 monitors might be explained through biomechanical theories of running. Research has indicated that when an exercise bout is adjusted for body dimensions, the movement pattern is more economical (Maliszewski and Freedson, 1996). It could be that at high speeds, the running motion was more fluid and efficient, with a more even stride frequency than at slower running speeds. As a result, there would be less minute-to-minute variation in accelerometer counts during fast running speeds.

In the AMP model, within-instrument variation was only significantly different in the right device ($p<0.05$). This device had the highest and lowest variation at mid-range speeds (i.e., 7 km/h and 6 km/h, respectively). The AMP is worn on the ankle and detects a count every time there is a heel-strike (Armstrong et al., 2004). The speed

6 km/h was a condition in which all participants walked. It could be that heel-strikes were better detected at this speed. The speed 7 km/h was a condition chosen for the most part by the youngest individuals as the treadmill run. The biomechanics of treadmill walking and running are very different, running being described as a series of "bouncing impacts", where there is more time spent in the aerial phase in comparison to walking (Farley and Ferris, 1998). As a result of this idea, more variability in heel-strikes may have occurred, leading to greater intra-device variation at this speed in the AMP.

In order to compare intra-device reliability between accelerometer models across all speeds, overall mean weighted coefficients were calculated (see Figure 3.4). Weighted coefficients were calculated because the number of cases of good data (i.e., N) was different among accelerometer models. The results indicated that intra-device variation in left monitors was lowest in the Actical (CV% = 3.7), and increased from the AMP (CV = 4.3%) to the RT3 (CV = 7.4%) to the MTI (CV = 8.7%). In the right devices, intra-device variation was lowest in the AMP (CV% = 2.8) and increased from the Actical (CV = 3.8%) to the MTI (CV = 7.2%) to the RT3 (CV = 7.8%). These results must be interpreted with caution however, as the amount of good data available for intra-device reliability analyses differed between models. Only 56.4% of data was available for the AMP model; data was eliminated if "0" counts were displayed or intra-device variation was greater than 40%. If all data from the AMP were used for these analyses, intra-device variation would have been significantly greater in this model compared to others. The Actical, MTI, and RT3 models all had a much greater percentage of good data available (i.e., 85.1%, 89.8%, and 99.6%, respectively). For all models, right devices also provided a greater percentage of good data. If these points are taken into consideration, it appears that the Actical may have produced the least amount of intra-device variation, followed by the MTI and the RT3, which were similar.

4.2.1.1 Comparison of intra-device reliability results to pilot testing

In the pilot testing that occurred prior to this research project (see Table 2.1), 15 devices (5 Actical, 5 MTI, and 5 RT3) were subjected to six different conditions of varying acceleration (i.e., 4.9, 9.81, 12.26 m/s^2) and frequency (1.5, 2.0, and 2.5 Hz). Intra-device variation in the Actical across all conditions was lower (i.e., CV-intra = 0.4%) than observed in this study, a difference of 3.4%. Intra-device variation in the MTI was also lower (i.e., 4.1%) than observed in this study, a difference of 3.9%. In the RT3 however, intra-device variation was much greater in pilot testing (i.e., 46.4%), a difference of 38.8%. This research project assessed the intra-device variability of accelerometer models during treadmill walking and running, conditions that introduce greater error and therefore variability than experienced in the controlled setting used during pilot testing. The fact that intra-device variation in the RT3 was higher during pilot testing may be a result of its greater frequency range (i.e., 0.5 to 10 Hz), in which natural vibrations from the shaker plate could have been detected. Results from this research project indicate that these models produce very low intra-device variation in accelerometer counts in less controlled environments, which is encouraging and supports their use as reliable tools for physical activity measurement.

4.2.2 Inter-device reliability

In this study, inter-device variation in accelerometer counts was analyzed across speed and compared between models. Variation in accelerometer counts between left and right devices of the same model was lowest at a fast speed (i.e., 11 km/h) and highest at a slow speed (i.e., 4 km/h) for the Actical and RT3. In the model most sensitive to detecting vertical acceleration (i.e., Actical), these findings may be explained by a leveling off of accelerometer counts at higher speeds and stride frequencies, as less within-device variation in accelerometer counts at higher speeds would result in less inter-device variation in accelerometer counts. This idea does not explain why inter-device variation would be lowest in the RT3 at one of the fastest speeds in this study. Previous research with the RT3 has found that inter-device variability increased with increasing speed (Powell and Rowlands, 2004), which is in direct contrast to what was observed in this study. Previous research with uniaxial devices has also reported greater inter-device variation in accelerometer counts with speed (Brage et al., 2003c). In these studies, this may be explained by the fact that biomechanical differences between left and right hips predominated at faster speeds. In this study however, as alluded to previously, participants who were running at higher speeds may have had a more dynamic running motion, with less biomechanical variation between left and right hips, than what may have occurred at slower running speeds. It could also be that at higher speeds, more saturation data was detected (i.e., leveling-off of accelerometer counts), which reduced the amount of good data available for analyses. This may have indirectly reduced the inter-device variation in accelerometer counts.

When comparing inter-device variation in accelerometer counts across all speeds between the different models (see Figure 3.5), results indicated that variation was lowest in the AMP (CV = 3.3%), and increased from the Actical (CV = 3.8%) to the RT3 (CV = 7.6%) to the MTI (CV = 8.0%). Again, because of differences in the percentage of good available data, it appears that the Actical may have produced the least intra-device variation in accelerometer counts, followed by the RT3 and the MTI.

4.2.2.1 Comparison of inter-device reliability results to pilot testing

Pilot testing with these models prior to the study found that inter-device variation was lowest in the MTI (CV = 4.9%) and increased from the Actical (CV = 15.5%) to the RT3 (CV = 42.9%). When comparing inter-device variation between pilot testing and this research study, inter-device variation in accelerometer counts was lower in the MTI in pilot testing (i.e., a difference of 3.1%) and higher in the Actical and RT3 during pilot testing (i.e., differences of 11.7% and 35.3%, respectively). As discussed previously, pilot testing was performed in a controlled environment, whereas biomechanical issues encountered during treadmill walking and running may have contributed to greater inter-device variation in the MTI.

The results of this research project demonstrated that the magnitude of the intra- and inter- instrument reliability measures differed between the four accelerometer models employed, which supports the second hypothesis.

4.3 HYPOTHESIS THREE

According to the third hypothesis, the RT3, a triaxial device, would provide a more reliable and valid assessment of physical activity at greater speeds and therefore greater accelerations and step frequencies than the other activity monitors.

The reliability of the RT3 activity monitor was examined by calculating intra-device and inter-device variation in accelerometer counts across speed. The data indicates that intra-device variation was lowest at 11 km/h in both left and right-mounted devices ($p<0.05$), a speed that was associated with very high stride frequencies among participants in this study. When compared to the other models at this speed however, intra-device variation in the RT3 model appears to be the greatest (see Tables 3.5 and 3.6), with the exception of the left MTI. Inter-instrument variation in the RT3 was also lowest at 11 km/h ($p<0.05$), however between-device variation in the RT3 at this speed appears to be greater than the Actical and the AMP (see Table 3.7). In actuality, there were no significant differences in intra-device or inter-device variation between models at this speed ($p<0.05$).

The ability of the RT3 to provide a valid estimate of energy expenditure at high speeds and high stride frequencies was assessed by examining the difference in energy expenditure predicted by the RT3 and measured energy expenditure from expired gas analysis for these conditions. Figure 3.11 illustrates that the RT3 typically overestimated energy expenditure at speeds 1, 2, and 3 ($p<0.05$), however this overestimation was greatest during speed 3 ($p<0.05$), in which participants ran at a self-selected speed for 10 minutes in duration. For speed 3, the RT3 overestimated energy expenditure for 89.4 % of trials. For the same treadmill condition, the AMP and the Yamax underestimated energy expenditure for 100% of trials, while the Actical underestimated energy expenditure for 99.9% of trials. The MTI underestimated energy expenditure for 54.4 % of trials, and overestimated energy expenditure for 45.6 % of trials.

It is important to note that the RT3 had the most available good data when compared to all other models, with the exception of the Yamax, for speed 3. With this in mind, the mean overestimation in energy expenditure by the RT3 was 1.9 kcal/min (range of 7.6 kcal/min to -2.4 kcal/min), while the mean underestimation in the other models at this speed was -8.6 kcal/min (range of -19.8 kcal/min to 1.1 kcal/min) for the AMP (based on 67 cases), -1.8 kcal/min (range of -6.6 kcal/min to 0.6 kcal/min) for the Actical (based on 61 cases) and -6.9 kcal/min (range of –14.5 kcal/min to 2.9 kcal/min) for the Yamax (based on 85 cases). The MTI had a mean underestimation of -0.58 kcal/min (range of -16.6 kcal/min to 4.9 kcal/min; based on 79 cases). These results indicate that although the RT3 overestimated energy expenditure during treadmill running, when stride frequency was very high, the variability in predicted energy expenditure was not as great as in the MTI model. In addition, the RT3 rewarded participants for energy expended at higher speeds and stride frequencies, whereas the AMP, Actical, and Yamax activity monitors were unable to accurately capture energy expended under these conditions. Nonetheless, because the RT3 overestimated energy expenditure during treadmill running, predictions of energy expenditure under these conditions must be interpreted with caution.

4.3.1 Reliability of RT3 in past literature

Powell and Rowlands (2004) assessed the inter-device reliability of 8 RT3 activity monitors using a treadmill protocol that consisted of four 12-minute bouts of activity: walking (i.e., at 4 and 6 km/h) and running (i.e., at 8 and 10 km/h). Results revealed that during all speeds, variation in accelerometer counts between devices was very low (i.e., CV = 3.2%, 2.1%, 3.8%, and 1.5% for 4, 6, 8, and 10 km/h, respectively). In comparison, under the same speed conditions, inter-device variation in the RT3 in this research project was greater for all speeds (i.e., CV = 10.6%, 6.1%, 7.0%, and 6.8% for 4, 6, 8, and 10 km/h, respectively). A significant difference in sample size between the two research projects may explain these findings; Powell and Rowlands (2004) tested the reliability of RT3 monitors on only one individual on two separate occasions. In this research project, 86 participants performed three treadmill bouts of activity from a range of 4 to 12 km/h. Since findings from this research study have demonstrated that differences in participant characteristics, such as leg length, stride length and stride frequency, may affect accelerometer counts, there would be greater variation in these variables in a larger sample size, which might contribute to greater inter-device variation in accelerometer counts.

4.3.2 Validity of the RT3 in past literature

Rowlands and colleagues (2004) assessed the validity of RT3 monitors using a treadmill protocol, where 19 boys (age = 9.5 ± 0.8 years) and 15 men (age = 20.7 ± 1.4 years) walked at 4 and 6 km/h and ran at 8 and 10 km/h, each condition lasting 4 minutes in duration. Energy expenditure was measured using expired gas analysis and reported as scaled oxygen consumption (sVO_2) to reflect differences in body size between participants. The correlation between predicted energy expenditure and measured energy expenditure across all treadmill speeds was high ($R^2 = 0.69$, $p<0.01$), similar to what was reported in this research (i.e., $R^2 = 0.88$ for speeds 1, 2, and 3 combined). Previous research revealed that the Tritrac, a triaxial model, overestimated energy expenditure for treadmill walking (i.e., 3 mph, 4 mph) and jogging (i.e., 6 mph) (Welk et al., 2000a), which is consistent with the results from this study.

The results of this research project demonstrated that the RT3, a triaxial device, did provide a more reliable and valid assessment of physical activity at greater speeds and stride frequencies than the other monitors, supporting the third hypothesis.

4.4 BIOMECHANICAL EXPLANATIONS FOR VARIABILITY IN ACCELEROMETER DATA

4.4.1 Biomechanical differences in walking and running

4.4.1.1 Ground reaction force

An examination of the dynamics of walking and running is necessary when utilizing physical activity monitors to measure energy expenditure. The pattern of center of mass movements is very different between walking and running. Differences in ground reaction force can help interpret accelerometer data and predict energy expenditure during treadmill walking and running. Ground reaction force is simply the force exerted by the ground on the feet, and represents the acceleration of a body's center of mass during locomotion (Farley and Ferris, 1998). Ground reaction force patterns for walking and running are distinctly different. In walking, at least one foot is always in contact with the ground, and there are short phases when both feet are in contact with the ground. Running however, can be characterized by a series of bouncing impacts with the ground alternated with aerial phases in which neither foot contacts the ground (Farley and Ferris, 1998). As a result of these differences, the magnitude of the vertical component of the ground reaction force is significantly higher during running. The pattern of the horizontal component of the ground reaction force is similar though, negative in the first half of the stance phase (i.e., pushing backwards on the individual) and positive in the second half of the stance phase (i.e., pushing forward on the individual). In this study, there was an increase in accelerometer counts with increasing speed (i.e., from walking to running), which, according to this theory, is explained by a greater magnitude in the vertical component of the ground reaction force during running.

4.4.1.2 Contribution of horizontal and vertical power to total power during walking and running

The ratio of vertical to horizontal power across speed can also provide insight into variation in accelerometer counts detected in this study. Previous research indicates that vertical mechanical power is the largest component of total power below 4 km/h (Brage et al., 2003c). At faster walking speeds, horizontal power predominates and the vertical component increases only until the participant begins to run. Since vertical acceleration is constant across running speed and horizontal power contributes to a greater proportion of total power, accelerometers that are unable to assess the horizontal axis may produce a leveling-off of accelerometer counts.

In this project, it was demonstrated that accelerometer counts began to level off with increasing speed and stride frequency in devices only capable of, or most sensitive to, detecting vertical body acceleration (i.e., Actical and MTI). Past research has also noted a leveling-off of accelerometer counts at high treadmill running speeds in uniaxial devices (Brage et al., 2003c; Haymes and Byrnes, 1993), which support our findings. In this study, the leveling-off phenomenon did not occur in the RT3, a device that assesses body acceleration along three axes. This device had a much larger frequency range than both the Actical and the MTI, and therefore it was able to produce accelerometer counts at very high stride frequencies. Previous research has suggested that triaxial devices might be more capable of measuring physical activity and predicting energy expenditure at higher speeds (and greater stride frequencies) than uniaxial devices for these reasons (Bouten et al., 1994; Eston et al., 1998). As the results of this study are supported by past literature, it appears that triaxial devices might provide a more reliable and valid estimate of energy expenditure during treadmill running at very fast speeds.

4.4.1.3 Relationship between efficiency of treadmill locomotion and energy expenditure

It is well documented that the energy cost of locomotion relative to body size decreases with age (Rowland, 2005). When walking or running at the same speed, younger children have been found to consume more oxygen per kilogram of body mass in comparison to older children and adults (Astrand, 1952). Furthermore, the rate of rise in mass-specific energy demands increases as running velocity increases and body size decreases (Rowland, 2005). These findings can be partially explained by exercise economy (i.e., the amount of energy expended per kilogram at a given treadmill speed), which improves with age (Rowland, 2005).

In this study, differences in economy of movement among participants may provide explanation for trends in accelerometer data as well as measured and predicted energy expenditure. All participants were instructed to select speeds in which they were confident they could complete. Many participants (and typically the youngest ones) were unfamiliar with treadmill walking and running, and despite a familiarization period, some might have selected speeds that were too physically demanding. As a result, walking and running economy may have been compromised. This would have directly affected intra-device and inter-device variation in accelerometer counts. Furthermore, economy of movement may have contributed to biomechanical differences between the left and right hip during walking and running, adding further support to inter-device variation in accelerometer counts. Differences in ventilation among participants could have also affected economy of movement, therefore contributing to variance in accelerometer counts within each speed. Studies have shown that children have a higher ventilation rate than adults performing the same exercise bout (Bar-Or, 1983), a difference that is maximized at higher intensities and may influence economy (Rowland, 1996).

Research has noted that improvements in exercise economy with age are due to the fact that at a given velocity, younger and shorter individuals have a greater stride frequency than older and taller individuals (Rowland, 2005). A study of running economy in boys and men found that stride frequency was approximately 17% greater in boys than in men when running at 8.0, 8.8, and 9.6 km/h; running economy was greater in the men at all speeds, and the VO_2 cost of increasing running speed was less in the men (Rowland et al., 1987). However, when VO_2 per kilogram was expressed relative to a single stride, there were no differences in VO_2 between boys and men.

Although participants self-selected treadmill walking and running speeds, it was shown that within speeds, stride frequency decreased with age and leg length. According to this idea then, younger and shorter participants would have found it more physically demanding to exercise at a given speed than older and taller participants. This may have resulted in less efficient movement patterns for younger and shorter participants, which may have contributed to greater variation in accelerometer counts. This idea supports the results of this study, which demonstrated that leg length and stride frequency were directly associated with accelerometer counts at a given VO_2.

The results of this research project demonstrated that the RT3, a triaxial device, provided a more reliable and valid assessment of activity at greater speeds and therefore greater accelerations and step frequencies. Based on these findings, the third hypothesis was accepted.

4.5 CHOOSING A MODEL FOR SURVEILLANCE OF PHYSICAL ACTIVITY OVER TIME

The results of this study have indicated that when choosing a device to be used for longitudinal assessment of physical activity in the field, the choice really depends on the type of physical activity researchers are most interested in assessing. A summary of various characteristics associated with each activity monitor is presented in Table 4.1 in order to provide a more complete picture of its practicality for use in physical activity surveillance research.

Table 4.1 Characteristics of AMP, Actical, MTI, RT3, and Yamax activity monitors.

	AMP	**Actical**	**MTI**	**RT3**	**Yamax**
Data output	Counts/steps	Counts	Counts/steps	Counts	Steps
Orientation	N/A	Omnidirectional	Uniaxial	Triaxial	N/A
Size (cm)	7.1 x 2.4 x 3.8	2.8 x 2.7 x 1.0	5.1 x 3.8 x 1.5	7.1 x 5.6 x 2.8	5.1 x 3.8 x 1.9
Weight (gm)	50	17	42.6	65.2	21.3
Placement	Ankle	Hip	Hip	Hip	Hip
Waterproof	Yes	Yes	Yes	No	No
Acceleration range (G)	± 50	0.05 – 2.0	± 2.13	0.05 – 2.0	N/A
Frequency range (Hz)	0 – 400	0.5 – 3.0	0.21 – 2.28	0.5 – 10	N/A
Amount of continuous data capture time	24 hours for 9 days at 1 minute intervals	22 days at 1 minute intervals	22 days at 1 minute intervals	21 days at 1 minute intervals	365 days +
Cost (US$) Device Reader Software	 $450.00 $800.00 (with reader)	 $450.00 $725.00 $500.00	 $389.00 N/A $200.00	 $500.00 (with reader and software)	 $24.95
Intra-device reliability (left hip; CV%)	4.3	3.7	8.7	7.4	9.1
Intra-device reliability (right hip; CV%)	2.8	3.8	7.2	7.8	9.0
Inter-device reliability (CV%)	3.3	3.8	8.0	7.6	0.3
Validity	Underestimates kcal/min	Underestimates kcal/min	Underestimates and overestimates kcal/min	Overestimates kcal/min	Underestimates kcal/min
Percent (%) of good data collected	56.4	85.1	89.8	99.6	100
Researcher usability	Good	Excellent	Good	Excellent	Excellent
Participant usability	Excellent	Excellent	Excellent	Fair	Excellent

If researchers are most interested in assessing energy expended primarily through walking, it appears that the Yamax pedometer would provide the most reliable assessment of steps over time when compared to the AMP monitor. This assumption is based on the fact that the AMP provided a lower percentage of good data to be used for analyses (i.e., 56.4%) when compared to the Yamax (i.e., 100%). It could be that the AMP monitor is very sensitive to placement, and did not report complete data (i.e., "0" counts were present in the data set) simply because the device had shifted on the ankle during treadmill activity. Nevertheless, in normal wear, such shifting would be expected.

If researchers are interested in assessing energy expended during walking and running, then either the Actical or the RT3 would be a suitable choice. The reason that the MTI is not mentioned is that in this study, many problems occurred trying to initialize the devices (i.e., initialization attempts failed and/or resulted in a saturation of accelerometer counts). Furthermore, software programs designed to list accelerometer counts according to the time that they were recorded mismatched these two variables, creating obvious confusion when attempting to extract specific sequences of accelerometer counts. As a result of these problems, some MTI devices had to be sent back to the manufacturers and replaced with new devices, a process which took a lot of time and interrupted data collection. No problems were encountered with either the Actical or the RT3, although the Actical did produce saturation of accelerometer counts at very high speeds and stride frequencies. The RT3 was able to capture activity data at high speeds and high stride frequencies, which makes it a very suitable choice for researchers interested in measuring physical activity at very high running speeds.

Additional characteristics must also be assessed when deciding which activity monitor to use for physical activity measurement. The Actical is very small, waterproof and demonstrated very high intra-device and inter-device reliability across treadmill speeds in this study. The MTI is much larger than the Actical (although not as large as the RT3), yet was less reliable than the Actical and was associated with many problems. The RT3, although it appears it may provide more reliable and valid data at higher running speeds, is not waterproof and is much larger in size than the other models. In this study, some participants complained that the RT3 was in the way when they were running, with their hands hitting the device as their arms were swinging along side of their torso in a natural running motion. The large size of the RT3, when compared to the other models, was even more apparent on the youngest and smallest participants.

Researchers interested in assessing physical activity must also be aware of whether differences in accelerometer placement (i.e., left hip versus right hip) might confound data. Results from this study indicate that when considering each model separately, accelerometer counts from devices placed on the left and right hip were not significantly different at speeds 1, 2, and 3, with the exception of both the MTI and RT3 at speed 3 (see Figure 3.2). These findings correspond with previous research, which reported no significant differences in accelerometer counts between left and right hip-mounted devices (Powell et al., 2003; Trost et al., 1998). When utilizing accelerometers for longitudinal assessments of physical activity, researchers should still be consistent in the placement of these devices within the population of interest.

When deciding upon one of these models to use for longitudinal physical activity measurement, it is also important to choose a model that provides activity data that will be consistent across time. With continuing technological advances, newer accelerometers are being introduced into the market and those that already exist are undergoing adaptations to increase the range and ability of functions that they are able to provide for accurate physical activity monitoring. As a result of these changes, it may become difficult to compare accelerometer data collected over time. A more concrete measurement, such as a step, does not change over time, and therefore is directly comparable year after year in longitudinal research. Consequently, researchers may be best suited to selecting both an accelerometer and a pedometer so that when placed on an individual, a more complete picture of that individual's physical activity is generated, which can be compared across time. Considering this, it seems that a combination of the Actical accelerometer and the Yamax pedometer may capture the most reliable and valid profile of physical activity in a population, enabling accurate comparisons to be made over time.

4.6 CONCLUSION

Leg length and stride frequency was shown to directly influence variability in accelerometer data and the prediction of energy expenditure. At very high speeds and stride frequencies, accelerometer counts began to level off or become more variable in devices most sensitive to detecting body acceleration along the longitudinal axis of the body (i.e., Actical and MTI). This pattern did not occur in the RT3, a triaxial device, capable of also detecting acceleration in the horizontal plane, which predominates at higher running speeds.

Both intra-device and inter-device variation in accelerometer counts across all treadmill speeds was very low in all models utilized in this study, however results do need to be interpreted with caution due to the fact that the percent of good data available for analyses differed between all models. A large amount of data was eliminated due to malfunctions (i.e., AMP, MTI) and saturation (i.e., Actical and MTI), however if all data were used, intra-device and inter-device variation in accelerometer counts would have been significantly higher in these models.

The AMP, Actical, MTI, RT3, and Yamax all differed in their ability to predict energy expenditure. The AMP, Actical, and Yamax models tended to consistently underestimate energy expenditure across all treadmill speeds, while the MTI provided both underestimations and overestimations of energy expenditure across speed. The RT3 consistently overestimated energy expenditure during all treadmill conditions. Energy expenditure was both underestimated and overestimated to the greatest extent during speed 3, which involved treadmill running, for the tallest individuals. It becomes important to recognize these observations when interpreting energy expenditure data from these activity monitors under similar conditions in future research.

Accelerometer counts, when entered into regression equations with a combination of age, leg length and weight, were able to explain anywhere from 85 to 94 percent of variance in energy expenditure (kcal/min) measured through expired gas analysis. These findings suggest that these variables are important predictors of energy expenditure, and therefore should be entered into the predictive equations of AMP, Actical, MTI, RT3 and Yamax models if not already included.

4.7 RECOMMENDATIONS FOR FUTURE RESEARCH

The results of this study are limited to treadmill walking and running, which may not truly represent walking and running over natural terrain. Future research with these models needs to be conducted in field settings, where individuals are walking and running at speeds similar to those utilized in this study, in order to determine whether intra-device and inter-device variation in accelerometer counts differs. Validation of these models, using portable metabolic systems as the criterion standard, would be beneficial. Future research should also focus on improving the range of functions that accelerometers are able to provide in order to obtain a more complete picture of physical activity, which is a very complex behaviour. For example, in this study, the RT3, a triaxial device offered clear advantages for physical activity measurement at higher intensities, yet may not be a practical choice for surveillance research due the fact that it is large in size and not waterproof. Future triaxial devices that are smaller, waterproof and provide both step data and acceleration data would be useful. In addition, these devices should also be able to detect accelerations within a wider frequency range in order to prevent the leveling-off effect illustrated at high speeds and stride frequencies. Careful consideration should also be given towards designing a device that can be worn continuously by an individual and does not disrupt normal daily functioning. Healey (1999) has suggested the development of small wearable computers that collect physical activity data or tiny sensors that monitor pulse, respiration rate, electromyography, and /or skinconductivity, time-phased with pictures from a small, wearable digital camera to provide a complete picture of the frequency, intensity, duration and type of physical activity. Another idea might be the use of gel packs that attach directly to the skin and house accelerometers, eliminating the chance that the wearer might remove the device during physical activity assessment. Addressing some of these suggestions will likely improve the quality of physical activity data that is measured.

LIST OF CITED LITERATURE

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APPENDIX A

ACKNOWLEDGEMENT AND APPROVAL OF ETHICS SUBMISSION

University of Saskatchewan
Biomedical Research Ethics Board (Bio-REB)

18-Jan-2005

Certificate of Approval

PRINCIPAL INVESTIGATOR	DEPARTMENT	Bio #
Mark S. Tremblay	Kinesiology	04-205

INSTITUTION (S) WHERE RESEARCH WILL BE CARRIED OUT

College of Kinesiology
105 Gymnasium Place
Saskatoon SK S7N 5C2

SUB-INVESTIGATOR(S)

Michelle Stone

SPONSORING AGENCIES

TITLE:

Protocol The Effect of Leg Length and Stride Frequency on Accelerometer Data: An Intra- Inter-instrument Reliablity Study

ORIGINAL APPROVAL DATE	CURRENT EXPIRY DATE
05-Oct-2004	01-Oct-2005

CERTIFICATION UPDATE

Adult Consent Form v.2 (17 Jan 05)
Participant Information and Assent Form v.2 (17 Jan 05)
Advertisement v.1 (17 Jan 05)

APPROVED ON

18-Jan-2005

CERTIFICATION

The University of Saskatchewan Biomedical Research Ethics Board (Bio- REB) has reviewed the above-named research project including the protocol and consent form, where applicable. The proposal was found to be acceptable on ethical grounds. The principal investigator has the responsibility of ensuring that the authorized research is carried out according to governing law. This Approval is valid for the above time period provided there is no change in experimental protocol or in the consent process.

ONGOING REVIEW REQUIREMENT(S) / REB ATTESTATION

In order to receive annual renewal, a status report must be submitted to the Chair for Committee consideration within one month of the current expiry date each year the study remains open, and upon study completion. Please refer to the following website for further instructions: http://www.usask.ca/research/ethics.shtml. In respect to clinical trials, the University of Saskatchewan Research Ethics Board complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations and carries out its functions in a manner consistent with Good Clinical Practices. This approval and the views of this REB have been documented in writing.

APPROVED

Barry D. McLennan

Barry D. McLennan, Ph.D., Chair
University of Saskatchewan
Biomedical Research Ethics Board (Bio-REB)

Please send all correspondence to:

Office of Research Services, University of Saskatchewan
Room 3403, 110 Gymnasium Place
Box 5000 RPO University
Saskatoon, SK S7N 4J8
Phone: (306) 966-4053 Fax: (306) 966-2069

APPENDIX B

PARTICIPANT RECRUITMENT POSTER

ATTENTION!

- **Would you like to be involved in innovative research at the U of S?**
- **Are you between the ages of 8 to 50?**
- **Participants are wanted for a study conducted as part of a Masters of Science thesis**
- **The study will be looking at objective measures of physical activity in children and adults titled:**

  "The effect of leg length and stride frequency on accelerometer data: an intra- and inter- instrument reliability study"

- **Study requires light to moderate treadmill walking/jogging trials**
- **Total testing time approximately 2 hours in length**

LOCATION:

PHYSICAL ACTIVITY COMPLEX

ROOM 344

RESTRICTIONS:
Any health complications that might interfere with treadmill walking/jogging

If interested, please contact:
Michelle Stone, MSc. Student
College of Kinesiology
University of Saskatchewan
(306) 966-1123
or email: michelle.stone@usask.ca

APPENDIX C

PARTICIPANT RECRUITMENT ADVERTISEMENT

– SASKATOON STAR PHOENIX

RESEARCH

PARTICIPANTS

Research participants are required for a university study on physical activity.

Ideal candidates will be:

Boys - 8 years minimum

- 4' to 5'6" in height

Girls - 8 years minimum

- 4' to 5' in height

Women –Any Age 6'+ in height

Session is 2 hours at U of S/PAC

Paid participation of $10.00

Please contact Michelle Stone at (306) 373-2070 or

michelle.stone@usask.ca

Approved by U of S Ethics Review Board

APPENDIX D

PARTICIPANT RECRUITMENT LETTER

-BRUNSKILL ELEMENTARY SCHOOL

January 7, 2005

Attention: Terry Kikcio
Principal – Brunskill Elementary School

My name is Michelle Stone and I am a Master's student in the College of Kinesiology at the University of Saskatchewan. I am writing to you, to ask your help, as I am trying to recruit participants for my thesis project. I am interested in testing boys and girls aged 8 to 18. I am looking for girls that are anywhere from 4'0 to 5'0 tall and boys who are anywhere from 4'0 to 5'6 tall.

My study is looking at the influence of leg length on energy expenditure as assessed by motion sensors (e.g. pedometers or step counters). Ideally I would like to recruit approximately 30 children from your school (15 males and 15 females) who fall within these height categories. Please find attached a copy of the consent form that describes my study in detail.

The study would require a total commitment of 2 hours, which would take place over one session in the Physical Activity Complex at the University of Saskatchewan (Room 344). All participants would be given $10.00 for volunteering for the study.

Would it be possible to place an advertisement for this study in the school newsletter, or arrange a time to visit with a few classes in person and pass out consent forms to those interested? If able to talk to the children directly, I would emphasize the fact that participation is voluntary, and it would be an out-of-school activity. All parents do have to give consent prior to their child's participation; in the form, there is a number to contact me directly should they have any questions.

Any assistance that you could offer me would be greatly appreciated. I will contact the school in the next couple of days to see if you feel you can help in any way. I know you are very busy, and I greatly appreciate any help you can offer me.

Thank you!

Michelle Stone
MSc Student
College of Kinesiology
University of Saskatchewan
(306) 966-1123 – work#

APPENDIX E

PARTICIPANT CONSENT FORM

UNIVERSITY OF SASKATCHEWAN
Adult Consent Form

You are invited to participate in a study called: *The effect of leg length and stride frequency on accelerometer data: an intra- and inter- instrument reliability study.* You do not have to participate in this study unless you want to, and if you choose to, you may leave at any time. Please read this form carefully, and feel free to contact the researcher to ask any questions that you might have.

Researcher: Michelle Stone, Primary Researcher, College of Kinesiology, University of Saskatchewan, (306) 966-1123.

Academic Supervisor: Dr. Mark Tremblay, Professor and Principal Investigator, College of Kinesiology, University of Saskatchewan/Statistics Canada, (613) 951-4385.

Purpose of the study:
The recent rise in the number of overweight and obese people has led many to suspect that people are less active. To investigate this idea, many researchers have looked at new ways to measure physical activity behaviour. Technology has provided these researchers with new tools (activity monitors and step counters) to assist in this work. As a researcher, I would like to test the ability of five different activity monitors for measuring physical activity.

Procedures:
Before data collection begins, you will be required to fill in a consent form and a health questionnaire. You will then be given a form to fill out that asks you about your normal physical activity participation. After this, you will be measured for both standing and sitting height. Next, your leg length will be measured. Measurements of weight, blood pressure, resting heart rate and skinfolds will also be taken. After these measurements are taken, a trained exercise tester will demonstrate to you how to walk and jog on a treadmill. You will then be allowed to practice on the treadmill so that you can become comfortable with it. After this, the exercise tester will help attach you to a device that measures the amount of oxygen that you take in, and the amount of energy that you expend during activity. You will be required to wear a form of headgear, which contains a valve that is held in your mouth, like a snorkel, a nose clip and a tube attached to a machine. This allows you to breathe through your mouth only into a tube that measures the gases in the air that you breathe. Once you are familiar with what is involved in the study, then you will have the chance to ask any questions that you might have, and have these questions answered ahead of time. At the end of this session, you will arrange a time with the researcher to come back for the testing part of the study.

When you first arrive at the testing session, you will be measured for your resting heart rate and blood pressure so that you can safely participate in treadmill exercise. A researcher will then attach all of the activity monitors to you, as well as the equipment that you were attached to in the last session you had (headgear, nose clips, etc.) to measure the amount of energy that you are using during activity. Once all devices have been attached, you will be asked to perform a treadmill warm-up for 3 minutes at a slow walking pace. After walking, you will stretch for 2 minutes in order to reduce muscle soreness. After the warm-up, you will be asked to walk or jog on the treadmill at different speeds, ranging from 3 to 12 km/h. All trials will take 10 minutes to complete, and you will have a 5-minute rest period between each trial. If you are not used to physical activity, there is a possibility that the treadmill exercise may cause your muscles to be a little sore for about 1-2 days after. Stretching after treadmill exercise will help this. The introduction and testing session is each expected to take about 1 hour for each session.

Reimbursement for Study Participation:
You will not be paid for taking part in the study, but will receive a $10.00 reimbursement for out-of-pocket expenses, such as parking, while participating in the study.

Consent form: Date___________________________

Signing this form shows that you ______________________________ agree to take part in the study: *The effect of leg length and stride frequency on accelerometer data: an intra- and inter-instrument reliability study.* It shows that you understand the following,

1. You understand the reason for this study and what will be asked of you of you take part.
2. Taking part in this study is totally up to you. If you don't want to, you don't have to answer the questions and/or have the measurements taken. You can leave the study at any time, without any penalty.
3. There are minimal risks involved with taking part in this study.
4. All data on individuals will be kept secret from anyone outside of the study and the report will summarize group results. No one will know your results, except the researchers.
5. If you withdraw from the study, then your data will be deleted if requested.
6. You have read and understood the information provided in this letter, and have been given a copy of that letter and the consent form.

__________________________ __________________________
Your name Your Signature

__________________________ __________________________
Researcher's Name Researcher's Signature

Michelle Stone, MSc.
College of Kinesiology
University of Saskatchewan
87 Campus Drive
Room 375, Physical Activity Complex
Saskatoon, SK S7N 5B2
(306) 966-1123

Who to Contact:
If you have any questions about this research program, please contact:
1. Dr. Mark Tremblay, Statistics Canada, (613) 951-4385

OR

2. Michelle Stone, College of Kinesiology, (306) 966-1123 or michelle.stone@usask.ca

If you have any questions about your rights as a research participant or concerns about your experiences while participating in this study, you should contact the Chair of the Biomedical Ethics Board, c/o the Office of Research Services, University of Saskatchewan at (306) 966-4053.

APPENDIX F

PARTICIPANT ASSENT FORM

UNIVERSITY OF SASKATCHEWAN
Participant Information and Assent Form

Title: The effect of leg length and stride frequency on accelerometer data: an intra- and inter-instrument reliability study

Researcher: Michelle Stone, Primary Researcher, College of Kinesiology, University of Saskatchewan, (306) 966-1123.

Academic Supervisor: Dr. Mark Tremblay, Professor and Principal Investigator, College of Kinesiology, University of Saskatchewan/Statistics Canada, (613) 951-4385.

Introduction:
This form may use words that you do not understand. Please ask the study researcher or her assistant to explain any words or information that you do not clearly understand. You are being asked to take part in a research study. This study will test how well the researchers are able to measure your activity. A research study is something like a science project in school. The people in charge of this study want to learn something new about how to measure a person's activity. When the study is over, they will be able to see how well they were able to measure your activity on the treadmill.

Description of the study:
In this study, you will be asked to walk or run on a treadmill, so that the researcher and their assistants can measure your activity. The researchers will show you how to get on and off of the treadmill, and let you get comfortable with it before they do the test. While you are on the treadmill, you will be asked to wear some devices on your waist and ankles that are going to help measure your activity. These devices are very small and in the shape of a box, and they are not very heavy to wear. The researcher will show you these tools and explain them to you in more detail before the test happens. In this study, either the researcher or one of their assistants will also be taking some simple health measures from you (height, weight, heart rate, etc.). You will also be asked to fill in a form that asks questions about your activity level.

You do not have to participate in this study unless you want to. If you say yes now, but change your mind later, you can say no to the researcher and that will still be O.K. If you decide not to take part in the study, no one will be upset. You can also ask questions at any time. If you or your parent/legal guardian have any questions or concerns, your parent/legal guardian can contact either Michelle Stone or Dr. Mark Tremblay at the numbers listed above.

Purpose:
The goal of this research is to see how well these tools (activity monitors and step counters) can measure your activity while you are on the treadmill.

Scope of the study:
We are asking children as young as age eight (8) to age eighteen (18) to be in this study. To be in this study, you need to come to the lab to get tested. The whole test will take about two hours. The researcher will tell you when you need to come to the lab.

Possible Benefits:
You will be a part of some interesting research that is going on at our University. You will also get some simple health measures from the data that is collected.

Confidentiality:
Any written information about you will be seen by the main researcher, her supervisor and her staff. People who make sure that the study is being done correctly may also see it. Reports based on the results of this study may be presented for scientific publication, but your identity will be kept confidential. If the information about the study is sent anywhere else, it will not have your name on it. A secret code, or your initials, will be used instead.

Reimbursement for Study Participation:
You will not be paid for taking part in the study, but will receive a $10.00 reimbursement for out-of-pocket expenses, such as parking, while participating in the study.

ASSENT
I have read this paper or have had it read to me. I understand what I have to do in this study and I agree to take part in it.

____
Child's Name (Print)

________________________________ ________________________
Child's Signature Date

____
Parent/Legal Guardian Name (Print)

________________________________ ________________________
Signature of Parent/Legal Guardian Date

Check which applies (to be completed by person administering assent):

- ❑ The participant is capable of reading and understanding the assent form and has signed above as documentation of assent to take part in the study.

- ❑ The participant is not capable of reading the assent form, however, the information was explained verbally to the participant who has verbally given assent to take part in this study.

____
Name of Person Administering Assent (Print)

____ ________________________
Signature of Person Administering Assent Date

Who to Contact:

If you have any questions about this research program, please contact:
1. Dr. Mark Tremblay, Statistics Canada, (613) 951-4385
2. Michelle Stone, College of Kinesiology, (306) 966-1123

If you have any questions about your rights as a research participant or concerns about your experiences while participating in this study, you should contact the Chair of the Biomedical Ethics Board, c/o the Office of Research Services, University of Saskatchewan at (306) 966-4053.

APPENDIX G

PHYSICAL ACTIVITY READINESS QUESTIONNAIRE

Physical Activity Readiness
Questionnaire - PAR-Q
(revised 1994)

PAR - Q & YOU

(A Questionnaire for People Aged 15 to 69)

Regular physical activity is fun and healthy, and increasingly more people are starting to become more active every day. Being more active is very safe for most people. However, some people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and you are not used to being very active, check with your doctor.

Common sense is your best guide when you answer these questions. Please read the questions carefully and answer each one honestly: check YES or NO.

YES	NO	
☐	☐	1. Has your doctor ever said that you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor?
☐	☐	2. Do you feel pain in your chest when you do physical activity?
☐	☐	3. In the past month, have you had chest pain when you were not doing physical activity?
☐	☐	4. Do you lose your balance because of dizziness or do you ever lose consciousness?
☐	☐	5. Do you have a bone or joint problem that could be made worse by a change in your physical activity?
☐	☐	6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?
☐	☐	7. Do you know of <u>any other reason</u> why you should not do physical activity?

If you answered

YES to one or more questions

Talk with your doctor by phone or in person BEFORE you start becoming much more physically active or BEFORE you have a fitness appraisal. Tell your doctor about the PAR-Q and which questions you answered YES.

- You may be able to do any activity you want — as long as you start slowly and build up gradually. Or, you may need to restrict your activities to those which are safe for you. Talk with your doctor about the kinds of activities you wish to participate in and follow his/her advice.
- Find out which community programs are safe and helpful for you.

NO to all questions

If you answered NO honestly to <u>all</u> PAR-Q questions, you can be reasonably sure that you can:

- start becoming much more physically active — begin slowly and build up gradually. This is the safest and easiest way to go.
- take part in a fitness appraisal — this is an excellent way to determine your basic fitness so that you can plan the best way for you to live actively.

DELAY BECOMING MUCH MORE ACTIVE:

- if you are not feeling well because of a temporary illness such as a cold or a fever — wait until you feel better; or
- if you are or may be pregnant — talk to your doctor before you start becoming more active.

Please note: If your health changes so that you then answer YES to any of the above questions, tell your fitness or health professional. Ask whether you should change your physical activity plan.

<u>Informed Use of the PAR-Q</u>: The Canadian Society for Exercise Physiology, Health Canada, and their agents assume no liability for persons who undertake physical activity, and if in doubt after completing this questionnaire, consult your doctor prior to physical activity.

You are encouraged to copy the PAR-Q but only if you use the entire form

NOTE: If the PAR-Q is being given to a person before he or she participates in a physical activity program or a fitness appraisal, this section may be used for legal or administrative purposes.

I have read, understood and completed this questionnaire. Any questions I had were answered to my full satisfaction.

NAME ______________________________

SIGNATURE ______________________________ DATE ______________________

SIGNATURE OF PARENT ______________________________ WITNESS ______________________
or GUARDIAN (for participants under the age of majority)

continued on other side...

Supported by: Health Canada Santé Canada

...continued from other side

PAR - Q & YOU

Physical Activity Readiness Questionnaire - PAR-Q (revised 1994)

We know that being physically active provides benefits for all of us. Not being physically active is recognized by the Heart and Stroke Foundation of Canada as one of the four modifiable primary risk factors for coronary heart disease (along with high blood pressure, high blood cholesterol, and smoking). People are physically active for many reasons — play, work, competition, health, creativity, enjoying the outdoors, being with friends. There are also as many ways of being active as there are reasons. What we choose to do depends on our own abilities and desires. No matter what the reason or type of activity, physical activity can improve our well-being and quality of life. Well-being can also be enhanced by integrating physical activity with enjoyable healthy eating and positive self and body image. Together, all three equal VITALITY. So take a fresh approach to living. Check out the VITALITY tips below!

Active Living:

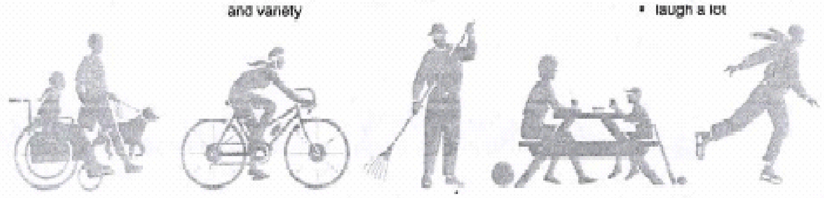
- accumulate 30 minutes or more of moderate physical activity most days of the week
- take the stairs instead of an elevator
- get off the bus early and walk home
- join friends in a sport activity
- take the dog for a walk with the family
- follow a fitness program

Healthy Eating:

- follow Canada's Food Guide to Healthy Eating
- enjoy a variety of foods
- emphasize cereals, breads, other grain products, vegetables and fruit
- choose lower-fat dairy products, leaner meats and foods prepared with little or no fat
- achieve and maintain a healthy body weight by enjoying regular physical activity and healthy eating
- limit salt, alcohol and caffeine
- don't give up foods you enjoy — aim for moderation and variety

Positive Self and Body Image:

- accept who you are and how you look
- remember, a healthy weight range is one that is realistic for your own body make-up (body fat levels should neither be too high nor too low)
- try a new challenge
- compliment yourself
- reflect positively on your abilities
- laugh a lot



Enjoy eating well, being active and feeling good about yourself. That's VITALITY.

FITNESS AND HEALTH PROFESSIONALS MAY BE INTERESTED IN THE INFORMATION BELOW.

The following companion forms are available for doctors' use by contacting the Canadian Society for Exercise Physiology (address below):

The **Physical Activity Readiness Medical Examination (PARmed-X)** - to be used by doctors with people who answer YES to one or more questions on the PAR-Q.

The **Physical Activity Readiness Medical Examination for Pregnancy (PARmed-X for PREGNANCY)** - to be used by doctors with pregnant patients who wish to become more active.

References:

Arraix, G.A., Wigle, D.T., Mao, Y. (1992). Risk Assessment of Physical Activity and Physical Fitness in the Canada Health Survey Follow-Up Study. **J. Clin. Epidemiol.** 45:4 419-428.

Mottola, M., Wolfe, L.A. (1994). Active Living and Pregnancy. In: A. Quinney, L. Gauvin, T. Wall (eds.), **Toward Active Living: Proceedings of the International Conference on Physical Activity, Fitness and Health.** Champaign, IL: Human Kinetics.

PAR-Q Validation Report, British Columbia Ministry of Health, 1978.

Thomas, S., Reading, J., Shephard, R.J. (1992). Revision of the Physical Activity Readiness Questionnaire (PAR-Q). **Can. J. Spt. Sci.** 17:4 338-345.

To order multiple printed copies of the PAR-Q, please contact the

Canadian Society for Exercise Physiology
185 Somerset St. West, Suite 202
Ottawa, Ontario CANADA K2P 0J2
Tel. (613) 234-3755 FAX: (613) 234-3565

The original PAR-Q was developed by the British Columbia Ministry of Health. It has been revised by an Expert Advisory Committee assembled by the Canadian Society for Exercise Physiology and Fitness Canada (1994).

Disponible en français sous le titre «Questionnaire sur l'aptitude à l'activité physique - Q-AAP (revisé 1994)».

Supported by: Health Canada Santé Canada

APPENDIX H

PHYSICAL ACTIVITY QUESTIONNAIRE FOR OLDER CHILDREN

Physical Activity Questionnaire for Children (Elementary School)

Name: ____________________ Age:__________ Sex: M______ F______

Grade:_________ Teacher:____________________

We are trying to find out about your level of physical activity from ***the last 7 days*** (in the last week). This includes sports or dance that make you sweat or make your legs feel tired, or games that make you breathe hard, like tag, skipping, running, climbing, and others.

Remember:
There are no right and wrong answers — this is not a test.
Please answer all the questions as honestly and accurately as you can — this is very important.

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1. Physical activity in your spare time: Have you done any of the following activities in the past 7 days (last week)? If yes, how many times? (Mark only one circle per row.)

	No	1-2	3-4	5-6	7 times or more
Skipping	O	O	O	O	O
Rowing/canoeing	O	O	O	O	O
In-line skating	O	O	O	O	O
Tag	O	O	O	O	O
Walking for exercise	O	O	O	O	O
Bicycling	O	O	O	O	O
Jogging or running	O	O	O	O	O
Aerobics	O	O	O	O	O
Swimming	O	O	O	O	O
Baseball, softball	O	O	O	O	O
Dance	O	O	O	O	O
Football	O	O	O	O	O
Badminton	O	O	O	O	O
Skateboarding	O	O	O	O	O
Soccer	O	O	O	O	O
Street hockey	O	O	O	O	O
Volleyball	O	O	O	O	O
Floor hockey	O	O	O	O	O
Basketball	O	O	O	O	O
Ice skating	O	O	O	O	O
Cross-country skiing	O	O	O	O	O
Ice hockey/ringette	O	O	O	O	O
Other: ____________________	O	O	O	O	O
____________________	O	O	O	O	O

2. In the last 7 days, during your physical education (PE) classes, how often were you very active (playing hard, running, jumping, throwing)? (Check one only.)

   - I don't do PE .... ❍
   - Hardly ever .... ❍
   - Sometimes .... ❍
   - Quite often .... ❍
   - Always .... ❍

3. In the last 7 days, what did you do most of the time *at recess*? (Check one only.)

   - Sat down (talking, reading, doing schoolwork)... ❍
   - Stood around or walked around .... ❍
   - Ran or played a little bit .... ❍
   - Ran around and played quite a bit .... ❍
   - Ran and played hard most of the time .... ❍

4. In the last 7 days, what did you normally do *at lunch* (besides eating lunch)? (Check one only.)

   - Sat down (talking, reading, doing schoolwork).. ❍
   - Stood around or walked around .... ❍
   - Ran or played a little bit .... ❍
   - Ran around and played quite a bit .... ❍
   - Ran and played hard most of the time .... ❍

5. In the last 7 days, on how many days *right after school*, did you do sports, dance, or play games in which you were very active? (Check one only.)

   - None .... ❍
   - 1 time last week .... ❍
   - 2 or 3 times last week .... ❍
   - 4 times last week .... ❍
   - 5 times last week .... ❍

6. In the last 7 days, on how many *evenings* did you do sports, dance, or play games in which you were very active? (Check one only.)

   - None .... ❍
   - 1 time last week .... ❍
   - 2 or 3 times last week .... ❍
   - 4 or 5 last week .... ❍
   - 6 or 7 times last week .... ❍

7. *On the last weekend*, how many times did you do sports, dance, or play games in which you were very active? (Check one only.)

None .... ❍
1 time .... ❍
2 — 3 times .... ❍
4 — 5 times .... ❍
6 or more times .... ❍

8. Which *one* of the following describes you best for the last 7 days? Read *all five* statements before deciding on the *one* answer that describes you.

A. All or most of my free time was spent doing things that involve little physical effort .... ❍

B. I sometimes (1 — 2 times last week) did physical things in my free time (e.g. played sports, went running, swimming, bike riding, did aerobics) .... ❍

C. I often (3 — 4 times last week) did physical things in my free time .... ❍

D. I quite often (5 — 6 times last week) did physical things in my free time... ❍

E. I very often (7 or more times last week) did physical things in my free time .... ❍

9. Mark how often you did physical activity (like playing sports, games, doing dance, or any other physical activity) for each day last week.

	None	Little bit	Medium	Often	Very often
Monday	❍	❍	❍	❍	❍
Tuesday	❍	❍	❍	❍	❍
Wednesday	❍	❍	❍	❍	❍
Thursday	❍	❍	❍	❍	❍
Friday	❍	❍	❍	❍	❍
Saturday	❍	❍	❍	❍	❍
Sunday	❍	❍	❍	❍	❍

10. Were you sick last week, or did anything prevent you from doing your normal physical activities? (Check one.)

Yes .... ❍
No .... ❍

If Yes, what prevented you? ______________________________

APPENDIX I

HEALTHY PHYSICAL ACTIVITY PARTICIPATION QUESTIONNAIRE

FIGURE 4-7 **HEALTHY PHYSICAL ACTIVITY PARTICIPATION**

DETERMINING THE HEALTH BENEFITS OF YOUR PHYSICAL ACTIVITY PARTICIPATION IS AS EASY AS A, B, C …

A. Answer the following questions:

#1 Frequency

Over a typical seven-day period (one week), how many times do you engage in physical activity that is sufficiently prolonged and intense to cause sweating and a rapid heart beat?

- ☐ At least three times
- ☐ Normally once or twice
- ☐ Rarely or never

#2 Intensity

When you engage in physical activity, do you have the impression that you:

- ☐ Make an intense effort
- ☐ Make a moderate effort
- ☐ Make a light effort

#3 Perceived Fitness

In a general fashion, would you say that your current physical fitness is:

- ☐ Very Good
- ☐ Good
- ☐ Average
- ☐ Poor
- ☐ Very Poor

B. Circle your score for each answer and total your score.

Scoring of Questionnaire Responses

Item	Male	Female	Male	Female	Male	Female
#1 Frequency	Rarely or never		Normally once or twice		At least three times	
	0	0	2	3	3	5
#2 Intensity	Light effort		Moderate effort		Intense effort	
	0	0	1	2	3	3
#3 Perceived Fitness	Very Poor or Poor		Average		Good or Very Good	
	0	0	3	1	5	3

Total Score = ____________

C. Determine your health benefit rating based on your score from B.

Health Benefit Zone	Total Score
Excellent	9 – 11
Very Good	6 – 8
Good	4 – 5
Fair	1 – 3
Needs Improvement	0

APPENDIX J

ACTICAL DOWNLOAD SAMPLE

--------------- Subject and Device Settings ----------------

Identity:	SUBJECT 81	
Age:	10 years	
Gender:	Male	
Height:	136.6	cm
	53.8	inches
Weight:	26.9	kg
	59.3	lbs
Start Date:	14-Apr-2005	
Start Time:	16:45	
Device Serial Number:	C841057	

-----------------Analysis Settings -----------------

Light/Moderate Cutpoint:	0.01	kcals/min/kg
Moderate/Vigorous Cutpoint:	0.05	kcals/min/kg
Energy Expenditure Output	AEE	(Activity Energy Expenditure)
Subject Type (age level):	ADOLESCENT	
Device Location:	HIP	

------------------ Epoch-by-Epoch Data ----

Epoch#	Day#	Elapsed Seconds	Date	Time	Activity Counts	Energy Expenditure kcals/min/kg
1042	1	2280	14-Apr-2005	17:22	1315	0.051
1043	1	2340	14-Apr-2005	17:23	1469	0.053
1044	1	2400	14-Apr-2005	17:24	1552	0.054
1045	1	2460	14-Apr-2005	17:25	1415	0.052
1046	1	2520	14-Apr-2005	17:26	1442	0.052
1047	1	2580	14-Apr-2005	17:27	1524	0.053
1048	1	2640	14-Apr-2005	17:28	1469	0.053
1054	1	3000	14-Apr-2005	17:34	2629	0.067
1055	1	3060	14-Apr-2005	17:35	2674	0.068
1056	1	3120	14-Apr-2005	17:36	2454	0.065
1057	1	3180	14-Apr-2005	17:37	2540	0.066
1058	1	3240	14-Apr-2005	17:38	2584	0.067
1059	1	3300	14-Apr-2005	17:39	2584	0.067
1060	1	3360	14-Apr-2005	17:40	2584	0.067
1074	1	4200	14-Apr-2005	17:54	10220	0.164
1075	1	4260	14-Apr-2005	17:55	8854	0.147
1076	1	4320	14-Apr-2005	17:56	9590	0.156
1077	1	4380	14-Apr-2005	17:57	9900	0.16
1078	1	4440	14-Apr-2005	17:58	10220	0.164
1079	1	4500	14-Apr-2005	17:59	10384	0.166
1080	1	4560	14-Apr-2005	18:00	10550	0.168

APPENDIX K

AMP DOWNLOAD SAMPLE

Time of Day	Energy Expenditure			Step Count			Distance [m]			Locomotion Details		
	Ave MET Value	**Total [Cal]**	Locomotion [Cal]	**Total Steps**	Steps	Active Steps	**Total Distance**	Distance	Active Distance	**Ave Speed [m/s]**	Ave Step Length [m]	Ave Cadence [steps/min]
17:22:00 - 17:23:00	2.81	**2.1**	2.10	**108**	108	0	**65**	65	0	**1.08**	0.60	108.00
17:23:00 - 17:24:00	2.81	**2.1**	2.10	**106**	106	0	**63**	63	0	**1.05**	0.59	106.00
17:24:00 - 17:25:00	2.81	**2.1**	2.10	**104**	104	0	**65**	65	0	**1.08**	0.63	104.00
17:25:00 - 17:26:00	2.81	**2.1**	2.10	**106**	106	0	**65**	65	0	**1.08**	0.61	106.00
17:26:00 - 17:27:00	2.81	**2.1**	2.10	**106**	106	0	**67**	67	0	**1.12**	0.63	106.00
17:27:00 - 17:28:00	2.81	**2.1**	2.10	**104**	104	0	**65**	65	0	**1.08**	0.63	104.00
17:28:00 - 17:29:00	2.81	**2.1**	2.10	**104**	104	0	**65**	65	0	**1.08**	0.63	104.00
17:34:00 - 17:35:00	3.21	**2.4**	2.40	**124**	124	0	**77**	77	0	**1.28**	0.62	124.00
17:35:00 - 17:36:00	3.35	**2.5**	2.50	**122**	122	0	**80**	80	0	**1.33**	0.66	122.00
17:36:00 - 17:37:00	3.35	**2.5**	2.50	**118**	118	0	**79**	79	0	**1.32**	0.67	118.00
17:37:00 - 17:38:00	3.35	**2.5**	2.50	**120**	120	0	**76**	76	0	**1.27**	0.63	120.00
17:38:00 - 17:39:00	3.35	**2.5**	2.50	**120**	120	0	**80**	80	0	**1.33**	0.67	120.00
17:39:00 - 17:40:00	3.48	**2.6**	2.60	**116**	116	0	**80**	80	0	**1.33**	0.69	116.00
17:40:00 - 17:41:00	3.48	**2.6**	2.60	**118**	118	0	**81**	81	0	**1.35**	0.69	118.00
17:54:00 - 17:55:00	4.96	**3.7**	3.70	**160**	160	0	**99**	99	0	**1.65**	0.62	160.00
17:55:00 - 17:56:00	5.22	**3.9**	3.90	**162**	162	0	**103**	103	0	**1.72**	0.64	162.00
17:56:00 - 17:57:00	5.22	**3.9**	3.90	**164**	164	0	**101**	101	0	**1.68**	0.62	164.00
17:57:00 - 17:58:00	4.82	**3.6**	3.60	**160**	160	0	**97**	97	0	**1.62**	0.61	160.00
17:58:00 - 17:59:00	5.09	**3.8**	3.80	**168**	168	0	**102**	102	0	**1.70**	0.61	168.00
17:59:00 - 18:00:00	5.09	**3.8**	3.80	**164**	164	0	**101**	101	0	**1.68**	0.62	164.00
18:00:00 - 18:01:00	5.22	**3.9**	3.90	**154**	154	0	**102**	102	0	**1.70**	0.66	154.00

APPENDIX L

MTI DOWNLOAD SAMPLE

------------ Data File Created By ActiSoft -----------
Serial Number: SN11673
Start Time 16:15:00
Start Date 04/14/2005
Cycle Period (hh:mm:ss) 00:01:00
Download Time 18:20:01
Download Date 04/14/2005
Current Memory Address: 248
Battery Life Remaining: 3302 hrs Mode = 1

4/14/2005 17:22:00	1789
4/14/2005 17:23:00	1906
4/14/2005 17:24:00	2106
4/14/2005 17:25:00	2255
4/14/2005 17:26:00	2028
4/14/2005 17:27:00	2140
4/14/2005 17:28:00	2285
4/14/2005 17:34:00	3267
4/14/2005 17:35:00	3288
4/14/2005 17:36:00	3440
4/14/2005 17:37:00	3442
4/14/2005 17:38:00	3376
4/14/2005 17:39:00	3544
4/14/2005 17:40:00	3636
4/14/2005 17:54:00	6770
4/14/2005 17:55:00	7525
4/14/2005 17:56:00	6950
4/14/2005 17:57:00	7371
4/14/2005 17:58:00	7236
4/14/2005 17:59:00	7662
4/14/2005 18:00:00	8036

APPENDIX M

RT3 DOWNLOAD SAMPLE

Device Info:	RT3				
ATR Serial#	C0003928				
ATR Hardware Rev	0.1				
ATR Firmware Rev	0.6				
ATR CoBrand	0				
User Info:					
User ID	SUBJECT 81				
User Height	53	Inches			
User Weight	59	Lb			
User Age	10				
User Gender	0	Male			
User AMR	0.7893	Calories per Minute			
Test Info:					
Notes	right hip				
Activity Data:					
Download Time	4/14/2005	18:25:07			
Start Time	4/14/2005	16:45:00			
Format	4	VM 1 Minute			
Number Readings	100				

Entry	Date	Time	Total Calories	Activity Calories	VM
38	4/14/2005	17:22:00	2.081	1.2917	1294
39	4/14/2005	17:23:00	2.2518	1.4625	1465
40	4/14/2005	17:24:00	2.1679	1.3786	1381
41	4/14/2005	17:25:00	2.0631	1.2738	1276
42	4/14/2005	17:26:00	2.112	1.3227	1325
43	4/14/2005	17:27:00	2.113	1.3237	1326
44	4/14/2005	17:28:00	2.2757	1.4864	1489
50	4/14/2005	17:34:00	2.7239	1.9346	1938
51	4/14/2005	17:35:00	3.1123	2.323	2327
52	4/14/2005	17:36:00	3.1342	2.3449	2349
53	4/14/2005	17:37:00	1.9313	1.142	1144
54	4/14/2005	17:38:00	2.7199	1.9306	1934
55	4/14/2005	17:39:00	2.9436	2.1543	2158
56	4/14/2005	17:40:00	2.7589	1.9696	1973
70	4/14/2005	17:54:00	5.7158	4.9265	4935
71	4/14/2005	17:55:00	5.7118	4.9225	4931
72	4/14/2005	17:56:00	6.3197	5.5304	5540
73	4/14/2005	17:57:00	6.0692	5.2799	5289
74	4/14/2005	17:58:00	6.169	5.3797	5389
75	4/14/2005	17:59:00	5.8645	5.0752	5084
76	4/14/2005	18:00:00	6.4855	5.6962	5706